autogluon_each_location

October 21, 2023

1 Config

[1]:
```
# config

label = 'y'
metric = 'mean_absolute_error'
time_limit = 60*60
presets = 'best_quality'

do_drop_ds = True
# hour, dayofweek, dayofmonth, month, year
use_dt_attrs = []#["hour", "year"]
use_estimated_diff_attr = False
use_is_estimated_attr = True

to_drop = ["snow_drift:idx", "snow_density:kgm3", "wind_speed_w_1000hPa:ms",␣
 ↪"dew_or_rime:idx", "prob_rime:p", "fresh_snow_12h:cm", "fresh_snow_24h:cm",␣
 ↪"wind_speed_u_10m:ms", "wind_speed_v_10m:ms", "snow_melt_10min:mm",␣
 ↪"rain_water:kgm2", "dew_point_2m:K", "precip_5min:mm", "absolute_humidity_2m:
 ↪gm3", "air_density_2m:kgm3"]#, "msl_pressure:hPa", "pressure_50m:hPa", ␣
 ↪"pressure_100m:hPa"]

#to_drop = ["snow_drift:idx", "snow_density:kgm3", "wind_speed_w_1000hPa:
 ↪ms",␣"dew_or_rime:idx", "prob_rime:p", "fresh_snow_12h:cm", "fresh_snow_24h:
 ↪cm",␣"wind_speed_u_10m:ms", "wind_speed_v_10m:ms", "snow_melt_10min:
 ↪mm",␣"rain_water:kgm2", "dew_point_2m:K", "precip_5min:mm",␣
 ↪"absolute_humidity_2m:gm3", "air_density_2m:kgm3"]

use_groups = False
n_groups = 8

auto_stack = False
num_stack_levels = 0
num_bag_folds = 8
num_bag_sets = 20

use_tune_data = True
```

```
use_test_data = False
tune_and_test_length = 0.5 # 3 months from end
holdout_frac = None
use_bag_holdout = True # Enable this if there is a large gap between score_val␣
↪and score_test in stack models.

sample_weight = None#'sample_weight' #None
weight_evaluation = False#
sample_weight_estimated = 1
sample_weight_may_july = 1

run_analysis = False

shift_predictions_by_average_of_negatives_then_clip = False
clip_predictions = True
shift_predictions = False
```

2 Loading and preprocessing

[2]:
```
import pandas as pd
import numpy as np



import warnings
warnings.filterwarnings("ignore")


def feature_engineering(X):
    # shift all columns with "1h" in them by 1 hour, so that for index 16:00,␣
↪we have the values from 17:00
    # but only for the columns with "1h" in the name
    #X_shifted = X.filter(regex="\dh").shift(-1, axis=1)
    #print(f"Number of columns with 1h in name: {X_shifted.columns}")


    columns = ['clear_sky_energy_1h:J', 'diffuse_rad_1h:J', 'direct_rad_1h:J',
               'fresh_snow_12h:cm', 'fresh_snow_1h:cm', 'fresh_snow_24h:cm',
               'fresh_snow_3h:cm', 'fresh_snow_6h:cm']

    # Filter rows where index.minute == 0
    X_shifted = X[X.index.minute == 0][columns].copy()

    # Create a set for constant-time lookup
    index_set = set(X.index)
```

```
    # Vectorized time shifting
    one_hour = pd.Timedelta('1 hour')
    shifted_indices = X_shifted.index + one_hour
    X_shifted.loc[shifted_indices.isin(index_set)] = X.loc[shifted_indices[shifted_indices.isin(index_set)]][columns]

    # Count
    count1 = len(shifted_indices[shifted_indices.isin(index_set)])
    count2 = len(X_shifted) - count1

    print("COUNT1", count1)
    print("COUNT2", count2)

    # Rename columns
    X_old_unshifted = X_shifted.copy()
    X_old_unshifted.columns = [f"{col}_not_shifted" for col in X_old_unshifted.columns]

    date_calc = None
    # If 'date_calc' is present, handle it
    if 'date_calc' in X.columns:
        date_calc = X[X.index.minute == 0]['date_calc']




    # resample to hourly
    print("index: ", X.index[0])
    X = X.resample('H').mean()
    print("index AFTER: ", X.index[0])

    X[columns] = X_shifted[columns]
    #X[X_old_unshifted.columns] = X_old_unshifted

    if date_calc is not None:
        X['date_calc'] = date_calc

    return X




def fix_X(X, name):
    # Convert 'date_forecast' to datetime format and replace original column with 'ds'
    X['ds'] = pd.to_datetime(X['date_forecast'])
    X.drop(columns=['date_forecast'], inplace=True, errors='ignore')
```

```python
    X.sort_values(by='ds', inplace=True)
    X.set_index('ds', inplace=True)


    X = feature_engineering(X)

    return X



def handle_features(X_train_observed, X_train_estimated, X_test, y_train):
    X_train_observed = fix_X(X_train_observed, "X_train_observed")
    X_train_estimated = fix_X(X_train_estimated, "X_train_estimated")
    X_test = fix_X(X_test, "X_test")


    if weight_evaluation:
        # add sample weights, which are 1 for observed and 3 for estimated
        X_train_observed["sample_weight"] = 1
        X_train_estimated["sample_weight"] = sample_weight_estimated
        X_test["sample_weight"] = sample_weight_estimated


    y_train['ds'] = pd.to_datetime(y_train['time'])
    y_train.drop(columns=['time'], inplace=True)
    y_train.sort_values(by='ds', inplace=True)
    y_train.set_index('ds', inplace=True)

    return X_train_observed, X_train_estimated, X_test, y_train




def preprocess_data(X_train_observed, X_train_estimated, X_test, y_train,␣
↪location):
    # convert to datetime
    X_train_observed, X_train_estimated, X_test, y_train =␣
↪handle_features(X_train_observed, X_train_estimated, X_test, y_train)

    if use_estimated_diff_attr:
        X_train_observed["estimated_diff_hours"] = 0
        X_train_estimated["estimated_diff_hours"] = (X_train_estimated.index -␣
↪pd.to_datetime(X_train_estimated["date_calc"])).dt.total_seconds() / 3600
        X_test["estimated_diff_hours"] = (X_test.index - pd.
↪to_datetime(X_test["date_calc"])).dt.total_seconds() / 3600
```

```
        X_train_estimated["estimated_diff_hours"] =␣
↪X_train_estimated["estimated_diff_hours"].astype('int64')
        # the filled once will get dropped later anyways, when we drop y nans
        X_test["estimated_diff_hours"] = X_test["estimated_diff_hours"].
↪fillna(-50).astype('int64')

    if use_is_estimated_attr:
        X_train_observed["is_estimated"] = 0
        X_train_estimated["is_estimated"] = 1
        X_test["is_estimated"] = 1

    # drop date_calc
    X_train_estimated.drop(columns=['date_calc'], inplace=True)
    X_test.drop(columns=['date_calc'], inplace=True)


    y_train["y"] = y_train["pv_measurement"].astype('float64')
    y_train.drop(columns=['pv_measurement'], inplace=True)
    X_train = pd.concat([X_train_observed, X_train_estimated])


    # clip all y values to 0 if negative
    y_train["y"] = y_train["y"].clip(lower=0)

    X_train = pd.merge(X_train, y_train, how="inner", left_index=True,␣
↪right_index=True)

    # print number of nans in y
    print(f"Number of nans in y: {X_train['y'].isna().sum()}")


    X_train["location"] = location
    X_test["location"] = location

    return X_train, X_test
# Define locations
locations = ['A', 'B', 'C']

X_trains = []
X_tests = []
# Loop through locations
for loc in locations:
    print(f"Processing location {loc}...")
    # Read target training data
    y_train = pd.read_parquet(f'{loc}/train_targets.parquet')

    # Read estimated training data and add location feature
```

```python
    X_train_estimated = pd.read_parquet(f'{loc}/X_train_estimated.parquet')

    # Read observed training data and add location feature
    X_train_observed= pd.read_parquet(f'{loc}/X_train_observed.parquet')

    # Read estimated test data and add location feature
    X_test_estimated = pd.read_parquet(f'{loc}/X_test_estimated.parquet')

    # Preprocess data
    X_train, X_test = preprocess_data(X_train_observed, X_train_estimated,␣
 ↪X_test_estimated, y_train, loc)

    X_trains.append(X_train)
    X_tests.append(X_test)

# Concatenate all data and save to csv
X_train = pd.concat(X_trains)
X_test = pd.concat(X_tests)
```

```
Processing location A…
COUNT1 29667
COUNT2 1
index:  2019-06-02 22:00:00
index AFTER:  2019-06-02 22:00:00
COUNT1 4392
COUNT2 2
index:  2022-10-28 22:00:00
index AFTER:  2022-10-28 22:00:00
COUNT1 702
COUNT2 18
index:  2023-05-01 00:00:00
index AFTER:  2023-05-01 00:00:00
Number of nans in y: 0
Processing location B…
COUNT1 29232
COUNT2 1
index:  2019-01-01 00:00:00
index AFTER:  2019-01-01 00:00:00
COUNT1 4392
COUNT2 2
index:  2022-10-28 22:00:00
index AFTER:  2022-10-28 22:00:00
COUNT1 702
COUNT2 18
index:  2023-05-01 00:00:00
index AFTER:  2023-05-01 00:00:00
Number of nans in y: 4
Processing location C…
```

```
COUNT1 29206
COUNT2 1
index:  2019-01-01 00:00:00
index AFTER:  2019-01-01 00:00:00
COUNT1 4392
COUNT2 2
index:  2022-10-28 22:00:00
index AFTER:  2022-10-28 22:00:00
COUNT1 702
COUNT2 18
index:  2023-05-01 00:00:00
index AFTER:  2023-05-01 00:00:00
Number of nans in y: 6059
```

2.1 Feature enginering

2.1.1 Remove anomalies

[3]:
```python
import numpy as np
import pandas as pd


# loop thorugh x train[y], keep track of streaks of same values and replace␣
↪them with nan if they are too long
# also replace nan with 0

import numpy as np

def replace_streaks_with_nan(df, max_streak_length, column="y"):
    for location in df["location"].unique():
        x = df[df["location"] == location][column].copy()

        last_val = None
        streak_length = 1
        streak_indices = []
        allowed = [0]
        found_streaks = {}

        for idx in x.index:
            value = x[idx]
            # if location == "B":
            #     continue

            if value == last_val and value not in allowed:
                streak_length += 1
                streak_indices.append(idx)
            else:
                streak_length = 1
```

```
                last_val = value
                streak_indices.clear()

            if streak_length > max_streak_length:
                found_streaks[value] = streak_length

                for streak_idx in streak_indices:
                    x[idx] = np.nan
                streak_indices.clear()  # clear after setting to NaN to avoid␣
↪setting multiple times
        df.loc[df["location"] == location, column] = x

        print(f"Found streaks for location {location}: {found_streaks}")

    return df


# deep copy of X_train into x_copy
X_train = replace_streaks_with_nan(X_train.copy(), 3, "y")
```

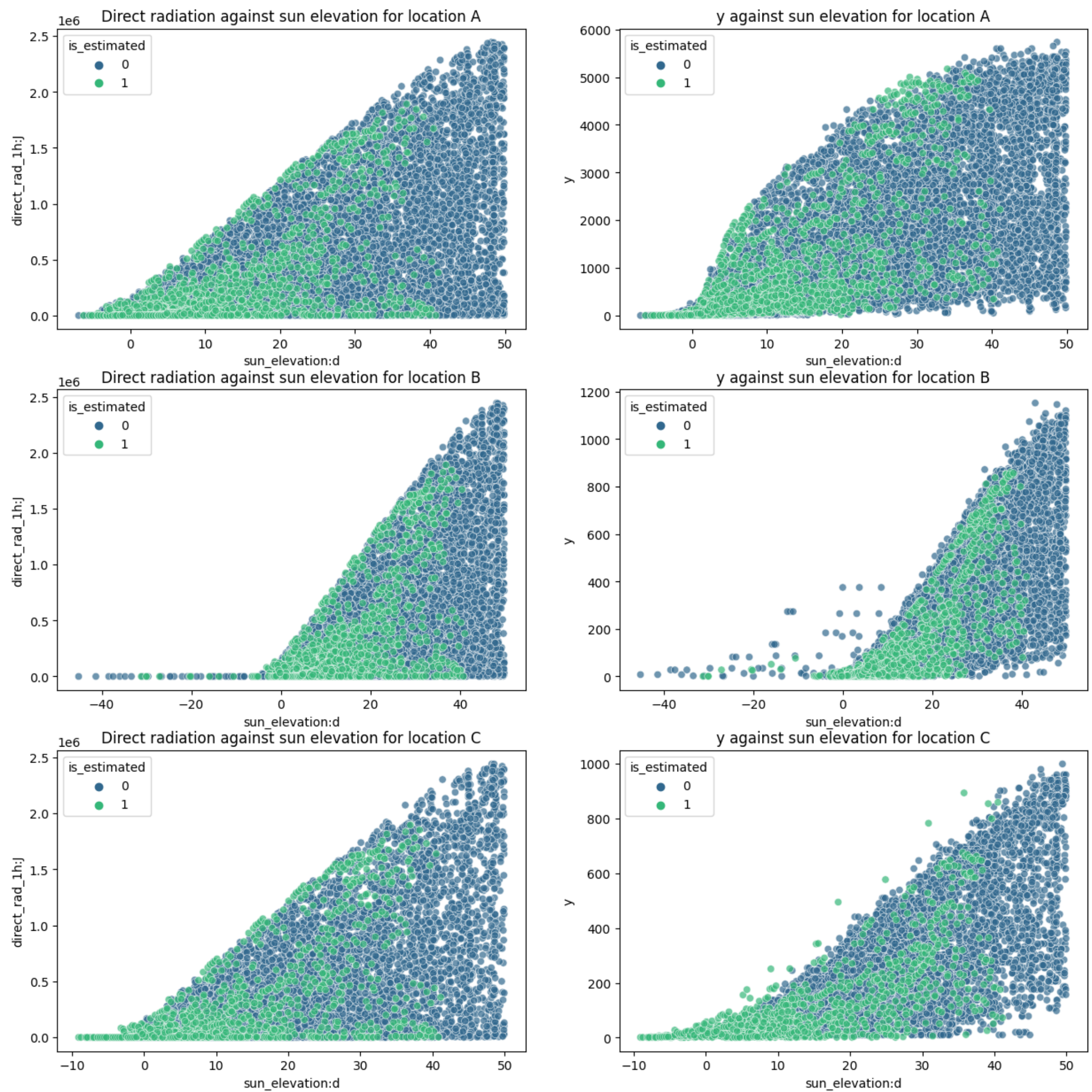
```
Found streaks for location A: {}
Found streaks for location B: {3.45: 28, 6.9: 7, 12.9375: 5, 13.8: 8, 276.0: 78,
18.975: 58, 0.8625: 4, 118.1625: 33, 34.5: 11, 183.7125: 1058, 87.1125: 7,
79.35: 34, 7.7625: 12, 27.6: 448, 273.41249999999997: 72, 264.78749999999997:
55, 169.05: 33, 375.1875: 56, 314.8125: 66, 76.7625: 10, 135.4125: 216, 81.9375:
202, 2.5875: 12, 81.075: 210}
Found streaks for location C: {9.8: 4, 29.400000000000002: 4, 19.6: 4}
```

[4]:
```
# print num rows
temprows = len(X_train)
X_train.dropna(subset=['y', 'direct_rad_1h:J', 'diffuse_rad_1h:J'],␣
↪inplace=True)
print("Dropped rows: ", temprows - len(X_train))
```

```
Dropped rows:  9293
```

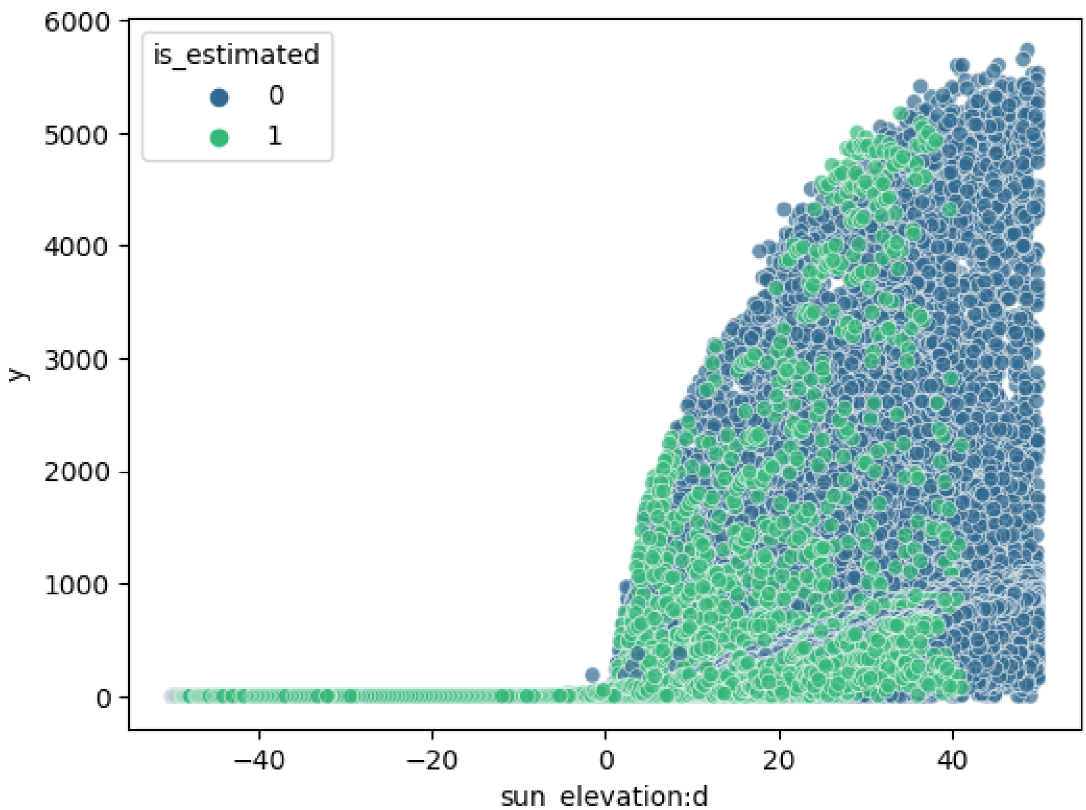
[5]:
```
import matplotlib.pyplot as plt
import seaborn as sns
# Filter out rows where y == 0
temp = X_train[X_train["y"] != 0]

# Plotting
fig, axes = plt.subplots(len(locations), 2, figsize=(15, 5 * len(locations)))

for idx, location in enumerate(locations):
    sns.scatterplot(ax=axes[idx][0], data=temp[temp["location"] == location],␣
↪x="sun_elevation:d", y="direct_rad_1h:J", hue="is_estimated",␣
↪palette="viridis", alpha=0.7)
```

```
    axes[idx][0].set_title(f"Direct radiation against sun elevation for␣
↪location {location}")

    sns.scatterplot(ax=axes[idx][1], data=temp[temp["location"] == location],␣
↪x="sun_elevation:d", y="y", hue="is_estimated", palette="viridis", alpha=0.7)
    axes[idx][1].set_title(f"y against sun elevation for location {location}")

# plt.tight_layout()
# plt.show()
```



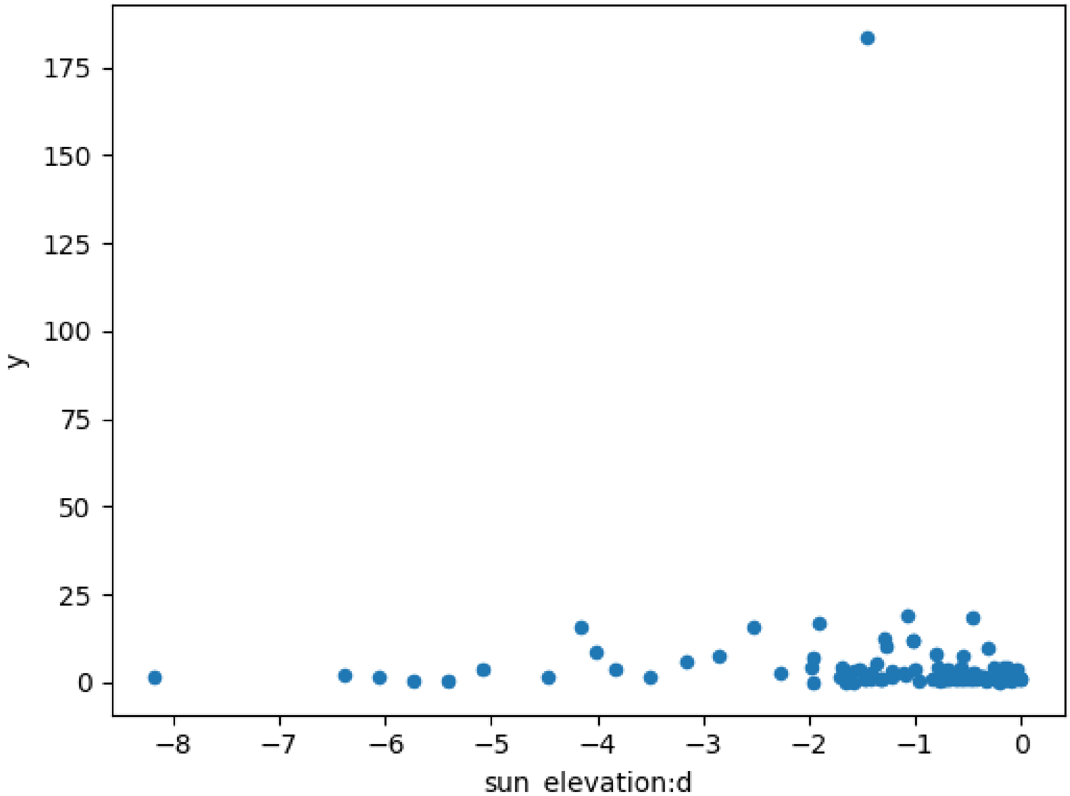
[6]:
```
thresh = 0.1
```

```
# Update "y" values to NaN if they don't meet the criteria
mask = (X_train["direct_rad_1h:J"] <= thresh) & (X_train["diffuse_rad_1h:J"] <=␣
 ↪thresh) & (X_train["y"] >= 0.1)
X_train.loc[mask, "y"] = np.nan

# Plot using sns scatterplot
sns.scatterplot(data=X_train, x="sun_elevation:d", y="y", hue="is_estimated",␣
 ↪palette="viridis", alpha=0.7)
plt.show()
```



[7]:
```
# location B count number of rows with y > 0 and sun_elevation:d < 0

condition = (X_train["location"] == "B") & (X_train["y"] > 0) &␣
 ↪(X_train["sun_elevation:d"] < 0)
bad = X_train[condition]

bad.plot.scatter(x="sun_elevation:d", y="y")
```

[7]: <AxesSubplot: xlabel='sun_elevation:d', ylabel='y'>




```
[8]: # print num rows
     temprows = len(X_train)
     X_train.dropna(subset=['y', 'direct_rad_1h:J', 'diffuse_rad_1h:J'],␣
      ↪inplace=True)
     print("Dropped rows: ", temprows - len(X_train))
```

```
Dropped rows:  1876
```

2.1.2 Other stuff

```
[9]: import numpy as np
     import pandas as pd

     for attr in use_dt_attrs:
         X_train[attr] = getattr(X_train.index, attr)
         X_test[attr] = getattr(X_test.index, attr)

     #print(X_train.head())
```

```python
# If the "sample_weight" column is present and weight_evaluation is True, multiply sample_weight with sample_weight_may_july if the ds is between 05-01 00:00:00 and 07-03 23:00:00, else add sample_weight as a column to X_train
if weight_evaluation:
    if "sample_weight" not in X_train.columns:
        X_train["sample_weight"] = 1

    X_train.loc[((X_train.index.month >= 5) & (X_train.index.month <= 6)) | ((X_train.index.month == 7) & (X_train.index.day <= 3)), "sample_weight"] *= sample_weight_may_july


print(X_train.iloc[200])
print(X_train[((X_train.index.month >= 5) & (X_train.index.month <= 6)) | ((X_train.index.month == 7) & (X_train.index.day <= 3))].head(1))



if use_groups:
    # fix groups for cross validation
    locations = X_train['location'].unique()  # Assuming 'location' is the name of the column representing locations

    grouped_dfs = []  # To store data frames split by location

    # Loop through each unique location
    for loc in locations:
        loc_df = X_train[X_train['location'] == loc]

        # Sort the DataFrame for this location by the time column
        loc_df = loc_df.sort_index()

        # Calculate the size of each group for this location
        group_size = len(loc_df) // n_groups

        # Create a new 'group' column for this location
        loc_df['group'] = np.repeat(range(n_groups), repeats=[group_size]*(n_groups-1) + [len(loc_df) - group_size*(n_groups-1)])

        # Append to list of grouped DataFrames
        grouped_dfs.append(loc_df)

    # Concatenate all the grouped DataFrames back together
    X_train = pd.concat(grouped_dfs)
    X_train.sort_index(inplace=True)
    print(X_train["group"].head())
```

```python
X_train.drop(columns=to_drop, inplace=True)
X_test.drop(columns=to_drop, inplace=True)

X_train.to_csv('X_train_raw.csv', index=True)
X_test.to_csv('X_test_raw.csv', index=True)
```

```
absolute_humidity_2m:gm3               7.625
air_density_2m:kgm3                   1.2215
ceiling_height_agl:m             3644.050049
clear_sky_energy_1h:J             2896336.75
clear_sky_rad:W                   753.849976
cloud_base_agl:m                 3644.050049
dew_or_rime:idx                          0.0
dew_point_2m:K                    280.475006
diffuse_rad:W                     127.475006
diffuse_rad_1h:J                  526032.625
direct_rad:W                           488.0
direct_rad_1h:J                  1718048.625
effective_cloud_cover:p            18.200001
elevation:m                              6.0
fresh_snow_12h:cm                        0.0
fresh_snow_1h:cm                         0.0
fresh_snow_24h:cm                        0.0
fresh_snow_3h:cm                         0.0
fresh_snow_6h:cm                         0.0
is_day:idx                               1.0
is_in_shadow:idx                         0.0
msl_pressure:hPa                 1026.775024
precip_5min:mm                           0.0
precip_type_5min:idx                     0.0
pressure_100m:hPa                1013.599976
pressure_50m:hPa                 1019.599976
prob_rime:p                              0.0
rain_water:kgm2                          0.0
relative_humidity_1000hPa:p        53.825001
sfc_pressure:hPa                 1025.699951
snow_density:kgm3                        NaN
snow_depth:cm                            0.0
snow_drift:idx                           0.0
snow_melt_10min:mm                       0.0
snow_water:kgm2                          0.0
sun_azimuth:d                     222.089005
sun_elevation:d                    44.503498
```

```
super_cooled_liquid_water:kgm2           0.0
t_1000hPa:K                       286.700012
total_cloud_cover:p                18.200001
visibility:m                        52329.25
wind_speed_10m:ms                        2.6
wind_speed_u_10m:ms                     -1.9
wind_speed_v_10m:ms                    -1.75
wind_speed_w_1000hPa:ms                  0.0
is_estimated                               0
y                                    4367.44
location                                   A
Name: 2019-06-11 13:00:00, dtype: object
                     absolute_humidity_2m:gm3  air_density_2m:kgm3  \
ds
2019-06-02 23:00:00                       7.7               1.2235

                     ceiling_height_agl:m  clear_sky_energy_1h:J  \
ds
2019-06-02 23:00:00           1689.824951                    0.0

                     clear_sky_rad:W  cloud_base_agl:m  dew_or_rime:idx  \
ds
2019-06-02 23:00:00              0.0       1689.824951              0.0

                     dew_point_2m:K  diffuse_rad:W  diffuse_rad_1h:J  …  \
ds                                                                   …
2019-06-02 23:00:00      280.299988            0.0               0.0  …

                     t_1000hPa:K  total_cloud_cover:p  visibility:m  \
ds
2019-06-02 23:00:00   286.899994                100.0  33770.648438

                     wind_speed_10m:ms  wind_speed_u_10m:ms  \
ds
2019-06-02 23:00:00               3.35                -3.35

                     wind_speed_v_10m:ms  wind_speed_w_1000hPa:ms  \
ds
2019-06-02 23:00:00                0.275                      0.0

                     is_estimated    y  location
ds
2019-06-02 23:00:00             0  0.0         A

[1 rows x 48 columns]
```

[10]:
```
# Create a plot of X_train showing its "y" and color it based on the value of␣
↪the sample_weight column.
if "sample_weight" in X_train.columns:
    import matplotlib.pyplot as plt
    import seaborn as sns
    sns.scatterplot(data=X_train, x=X_train.index, y="y", hue="sample_weight",␣
↪palette="deep", size=3)
    plt.show()
```

[11]:
```
def normalize_sample_weights_per_location(df):
    for loc in locations:
        loc_df = df[df["location"] == loc]
        loc_df["sample_weight"] = loc_df["sample_weight"] /␣
↪loc_df["sample_weight"].sum() * loc_df.shape[0]
        df[df["location"] == loc] = loc_df
    return df

import pandas as pd

def split_and_shuffle_data(input_data, num_bins, frac1):
    """
    Splits the input_data into num_bins and shuffles them, then divides the␣
↪bins into two datasets based on the given fraction for the first set.

    Args:
        input_data (pd.DataFrame): The data to be split and shuffled.
        num_bins (int): The number of bins to split the data into.
        frac1 (float): The fraction of each bin to go into the first output␣
↪dataset.

    Returns:
        pd.DataFrame, pd.DataFrame: The two output datasets.
    """
    # Validate the input fraction
    if frac1 < 0 or frac1 > 1:
        raise ValueError("frac1 must be between 0 and 1.")

    if frac1==1:
        return input_data, pd.DataFrame()

    # Calculate the fraction for the second output set
    frac2 = 1 - frac1

    # Calculate bin size
    bin_size = len(input_data) // num_bins

    # Initialize empty DataFrames for output
```

```
    output_data1 = pd.DataFrame()
    output_data2 = pd.DataFrame()

    for i in range(num_bins):
        # Shuffle the data in the current bin
        np.random.seed(i)
        current_bin = input_data.iloc[i * bin_size: (i + 1) * bin_size].
↪sample(frac=1)

        # Calculate the sizes for each output set
        size1 = int(len(current_bin) * frac1)

        # Split and append to output DataFrames
        output_data1 = pd.concat([output_data1, current_bin.iloc[:size1]])
        output_data2 = pd.concat([output_data2, current_bin.iloc[size1:]])

    # Shuffle and split the remaining data
    remaining_data = input_data.iloc[num_bins * bin_size:].sample(frac=1)
    remaining_size1 = int(len(remaining_data) * frac1)

    output_data1 = pd.concat([output_data1, remaining_data.iloc[:
↪remaining_size1]])
    output_data2 = pd.concat([output_data2, remaining_data.iloc[remaining_size1:
↪]])

    return output_data1, output_data2
```

[12]:
```
from autogluon.tabular import TabularDataset, TabularPredictor
data = TabularDataset('X_train_raw.csv')
# set group column of train_data be increasing from 0 to 7 based on time, the␣
↪first 1/8 of the data is group 0, the second 1/8 of the data is group 1, etc.
data['ds'] = pd.to_datetime(data['ds'])
data = data.sort_values(by='ds')

# # print size of the group for each location
# for loc in locations:
#     print(f"Location {loc}:")
#     print(train_data[train_data["location"] == loc].groupby('group').size())


# get end date of train data and subtract 3 months
#split_time = pd.to_datetime(train_data["ds"]).max() - pd.
↪Timedelta(hours=tune_and_test_length)
# 2022-10-28 22:00:00
split_time = pd.to_datetime("2022-10-28 22:00:00")
train_set = TabularDataset(data[data["ds"] < split_time])
test_set = TabularDataset(data[data["ds"] >= split_time])
```

```
# shuffle test_set and only grab tune_and_test_length percent of it, rest goes␣
↪to train_set
test_set, new_train_set = split_and_shuffle_data(test_set, 40,␣
↪tune_and_test_length)


print("Length of train set before adding test set", len(train_set))
# add rest to train_set
train_set = pd.concat([train_set, new_train_set])
print("Length of train set after adding test set", len(train_set))
print("Length of test set", len(test_set))




if use_groups:
    test_set = test_set.drop(columns=['group'])


tuning_data = None
if use_tune_data:
    if use_test_data:
        # split test_set in half, use first half for tuning
        tuning_data, test_data = [], []
        for loc in locations:
            loc_test_set = test_set[test_set["location"] == loc]
            # randomly shuffle the loc_test_set
            loc_tuning_data, loc_test_data =␣
↪split_and_shuffle_data(loc_test_set, 40, 0.5)
            tuning_data.append(loc_tuning_data)
            test_data.append(loc_test_data)
        tuning_data = pd.concat(tuning_data)
        test_data = pd.concat(test_data)
        print("Shapes of tuning and test", tuning_data.shape[0], test_data.
↪shape[0], tuning_data.shape[0] + test_data.shape[0])

    else:
        tuning_data = test_set
        print("Shape of tuning", tuning_data.shape[0])

    # ensure sample weights for your tuning data sum to the number of rows in␣
↪the tuning data.
    if weight_evaluation:
        tuning_data = normalize_sample_weights_per_location(tuning_data)
```

```
else:
    if use_test_data:
        test_data = test_set
        print("Shape of test", test_data.shape[0])


train_data = train_set

# ensure sample weights for your training (or tuning) data sum to the number of␣
↪rows in the training (or tuning) data.
if weight_evaluation:
    train_data = normalize_sample_weights_per_location(train_data)
    if use_test_data:
        test_data = normalize_sample_weights_per_location(test_data)


train_data = TabularDataset(train_data)
if use_tune_data:
    tuning_data = TabularDataset(tuning_data)
if use_test_data:
    test_data = TabularDataset(test_data)
```

```
Length of train set before adding test set 77247
Length of train set after adding test set 82582
Length of test set 5335
Shape of tuning 5335
```

3 Quick EDA

[13]:
```
if run_analysis:
    import autogluon.eda.auto as auto
    auto.dataset_overview(train_data=train_data, test_data=test_data,␣
↪label="y", sample=None)
```

[14]:
```
if run_analysis:
    auto.target_analysis(train_data=train_data, label="y", sample=None)
```

4 Modeling

[15]:
```
import os


# Get the last submission number
last_submission_number = int(max([int(filename.split('_')[1].split('.')[0]) for␣
↪filename in os.listdir('submissions') if "submission" in filename]))
print("Last submission number:", last_submission_number)
```

```
print("Now creating submission number:", last_submission_number + 1)

# Create the new filename
new_filename = f'submission_{last_submission_number + 1}'

hello = os.environ.get('HELLO')
if hello is not None:
    new_filename += f'_{hello}'

print("New filename:", new_filename)
```

```
Last submission number: 105
Now creating submission number: 106
New filename: submission_106
```

[16]:
```
predictors = [None, None, None]
```

[17]:
```
def fit_predictor_for_location(loc):
    print(f"Training model for location {loc}...")
    # sum of sample weights for this location, and number of rows, for both␣
 ↪train and tune data and test data
    if weight_evaluation:
        print("Train data sample weight sum:",␣
 ↪train_data[train_data["location"] == loc]["sample_weight"].sum())
        print("Train data number of rows:", train_data[train_data["location"]␣
 ↪== loc].shape[0])
        if use_tune_data:
            print("Tune data sample weight sum:",␣
 ↪tuning_data[tuning_data["location"] == loc]["sample_weight"].sum())
            print("Tune data number of rows:",␣
 ↪tuning_data[tuning_data["location"] == loc].shape[0])
        if use_test_data:
            print("Test data sample weight sum:",␣
 ↪test_data[test_data["location"] == loc]["sample_weight"].sum())
            print("Test data number of rows:", test_data[test_data["location"]␣
 ↪== loc].shape[0])
    predictor = TabularPredictor(
        label=label,
        eval_metric=metric,
        path=f"AutogluonModels/{new_filename}_{loc}",
        # sample_weight=sample_weight,
        # weight_evaluation=weight_evaluation,
        # groups="group" if use_groups else None,
    ).fit(
        train_data=train_data[train_data["location"] == loc].
 ↪drop(columns=["ds"]),
        time_limit=time_limit,
```

```
        # presets=presets,
        num_stack_levels=num_stack_levels,
        num_bag_folds=num_bag_folds if not use_groups else 2,# just put␣
↪somethin, will be overwritten anyways
        num_bag_sets=num_bag_sets,
        tuning_data=tuning_data[tuning_data["location"] == loc].
↪reset_index(drop=True).drop(columns=["ds"]) if use_tune_data else None,
        use_bag_holdout=use_bag_holdout,
        # holdout_frac=holdout_frac,
    )

    # evaluate on test data
    if use_test_data:
        # drop sample_weight column
        t = test_data[test_data["location"] == loc]#.
↪drop(columns=["sample_weight"])
        perf = predictor.evaluate(t)
        print("Evaluation on test data:")
        print(perf[predictor.eval_metric.name])

    return predictor

loc = "A"
predictors[0] = fit_predictor_for_location(loc)
```

```
Warning: path already exists! This predictor may overwrite an existing
predictor! path="AutogluonModels/submission_106_A"
Beginning AutoGluon training … Time limit = 3600s
AutoGluon will save models to "AutogluonModels/submission_106_A/"
AutoGluon Version:  0.8.2
Python Version:     3.10.12
Operating System:   Linux
Platform Machine:   x86_64
Platform Version:   #1 SMP Debian 5.10.197-1 (2023-09-29)
Disk Space Avail:   86.23 GB / 315.93 GB (27.3%)
Train Data Rows:    30718
Train Data Columns: 32
Tuning Data Rows:    2062
Tuning Data Columns: 32
Label Column: y
Preprocessing data …
AutoGluon infers your prediction problem is: 'regression' (because dtype of
label-column == float and many unique label-values observed).
        Label info (max, min, mean, stddev): (5733.42, 0.0, 674.18497,
1194.75343)
        If 'regression' is not the correct problem_type, please manually specify
the problem_type parameter during predictor init (You may specify problem_type
```

```
as one of: ['binary', 'multiclass', 'regression'])
Using Feature Generators to preprocess the data …
Fitting AutoMLPipelineFeatureGenerator…
        Available Memory:                    128709.8 MB
        Train Data (Original)  Memory Usage: 10.03 MB (0.0% of available memory)
        Inferring data type of each feature based on column values. Set
feature_metadata_in to manually specify special dtypes of the features.
        Stage 1 Generators:
                Fitting AsTypeFeatureGenerator…
                        Note: Converting 1 features to boolean dtype as they
only contain 2 unique values.
        Stage 2 Generators:
                Fitting FillNaFeatureGenerator…
        Stage 3 Generators:
                Fitting IdentityFeatureGenerator…
        Stage 4 Generators:
                Fitting DropUniqueFeatureGenerator…

Training model for location A…

        Stage 5 Generators:
                Fitting DropDuplicatesFeatureGenerator…
        Useless Original Features (Count: 2): ['elevation:m', 'location']
                These features carry no predictive signal and should be manually
investigated.
                This is typically a feature which has the same value for all
rows.
                These features do not need to be present at inference time.
        Types of features in original data (raw dtype, special dtypes):
                ('float', []) : 29 | ['ceiling_height_agl:m',
'clear_sky_energy_1h:J', 'clear_sky_rad:W', 'cloud_base_agl:m', 'diffuse_rad:W',
…]
                ('int', [])   :  1 | ['is_estimated']
        Types of features in processed data (raw dtype, special dtypes):
                ('float', [])     : 29 | ['ceiling_height_agl:m',
'clear_sky_energy_1h:J', 'clear_sky_rad:W', 'cloud_base_agl:m', 'diffuse_rad:W',
…]
                ('int', ['bool']) :  1 | ['is_estimated']
        0.1s = Fit runtime
        30 features in original data used to generate 30 features in processed
data.
        Train Data (Processed) Memory Usage: 7.64 MB (0.0% of available memory)
Data preprocessing and feature engineering runtime = 0.15s …
AutoGluon will gauge predictive performance using evaluation metric:
'mean_absolute_error'
        This metric's sign has been flipped to adhere to being higher_is_better.
The metric score can be multiplied by -1 to get the metric value.
        To change this, specify the eval_metric parameter of Predictor()
use_bag_holdout=True, will use tuning_data as holdout (will not be used for
```

```
early stopping).
User-specified model hyperparameters to be fit:
{
	'NN_TORCH': {},
	'GBM': [{'extra_trees': True, 'ag_args': {'name_suffix': 'XT'}}, {},
'GBMLarge'],
	'CAT': {},
	'XGB': {},
	'FASTAI': {},
	'RF': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
	'XT': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
	'KNN': [{'weights': 'uniform', 'ag_args': {'name_suffix': 'Unif'}},
{'weights': 'distance', 'ag_args': {'name_suffix': 'Dist'}}],
}
Fitting 11 L1 models …
Fitting model: KNeighborsUnif_BAG_L1 … Training model for up to 3599.85s of
the 3599.85s of remaining time.
	-192.4921	 = Validation score   (-mean_absolute_error)
	0.03s	 = Training   runtime
	0.36s	 = Validation runtime
Fitting model: KNeighborsDist_BAG_L1 … Training model for up to 3599.36s of
the 3599.36s of remaining time.
	-193.7334	 = Validation score   (-mean_absolute_error)
	0.03s	 = Training   runtime
	0.36s	 = Validation runtime
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 3598.9s of the
3598.9s of remaining time.
	Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
	-87.1023	 = Validation score   (-mean_absolute_error)
	28.11s	 = Training   runtime
	19.38s	 = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 3561.05s of the
3561.05s of remaining time.
	Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
	-91.8659	 = Validation score   (-mean_absolute_error)
	24.1s	 = Training   runtime
	5.77s	 = Validation runtime
Fitting model: RandomForestMSE_BAG_L1 … Training model for up to 3533.21s of
```

```
the 3533.21s of remaining time.
        -105.5385        = Validation score   (-mean_absolute_error)
        6.97s    = Training   runtime
        1.06s    = Validation runtime
Fitting model: CatBoost_BAG_L1 … Training model for up to 3522.98s of the
3522.98s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -100.1462        = Validation score   (-mean_absolute_error)
        192.88s  = Training   runtime
        0.09s    = Validation runtime
Fitting model: ExtraTreesMSE_BAG_L1 … Training model for up to 3328.94s of the
3328.93s of remaining time.
        -109.0236        = Validation score   (-mean_absolute_error)
        1.44s    = Training   runtime
        1.04s    = Validation runtime
Fitting model: NeuralNetFastAI_BAG_L1 … Training model for up to 3325.28s of
the 3325.27s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -106.1036        = Validation score   (-mean_absolute_error)
        37.75s   = Training   runtime
        0.47s    = Validation runtime
Fitting model: XGBoost_BAG_L1 … Training model for up to 3284.89s of the
3284.88s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -98.2997         = Validation score   (-mean_absolute_error)
        44.73s   = Training   runtime
        1.54s    = Validation runtime
Fitting model: NeuralNetTorch_BAG_L1 … Training model for up to 3236.46s of
the 3236.46s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -87.0716         = Validation score   (-mean_absolute_error)
        57.65s   = Training   runtime
        33.64s   = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 3009.72s of the
3009.72s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -92.0074         = Validation score   (-mean_absolute_error)
        43.25s   = Training   runtime
        8.82s    = Validation runtime
Fitting model: CatBoost_BAG_L1 … Training model for up to 2986.94s of the
2986.94s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
```

```
        -88.0041         = Validation score   (-mean_absolute_error)
        202.05s  = Training   runtime
        0.61s    = Validation runtime
Fitting model: LightGBMLarge_BAG_L1 … Training model for up to 2629.69s of the
2629.69s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -89.7934         = Validation score   (-mean_absolute_error)
        185.11s  = Training   runtime
        39.78s   = Validation runtime
Repeating k-fold bagging: 3/20
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 2522.3s of the
2522.3s of remaining time.
        Fitting 8 child models (S3F1 - S3F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -86.8236         = Validation score   (-mean_absolute_error)
        85.1s    = Training   runtime
        51.23s   = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 2486.69s of the
2486.69s of remaining time.
        Fitting 8 child models (S3F1 - S3F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -91.789  = Validation score   (-mean_absolute_error)
        65.11s   = Training   runtime
        12.29s   = Validation runtime
Fitting model: CatBoost_BAG_L1 … Training model for up to 2459.08s of the
2459.08s of remaining time.
        Fitting 8 child models (S3F1 - S3F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -99.4073         = Validation score   (-mean_absolute_error)
        568.06s  = Training   runtime
        0.26s    = Validation runtime
Fitting model: NeuralNetFastAI_BAG_L1 … Training model for up to 2269.67s of
the 2269.67s of remaining time.
        Fitting 8 child models (S3F1 - S3F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -104.9964        = Validation score   (-mean_absolute_error)
        112.57s  = Training   runtime
        1.44s    = Validation runtime
Fitting model: XGBoost_BAG_L1 … Training model for up to 2230.13s of the
2230.13s of remaining time.
        Fitting 8 child models (S3F1 - S3F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -97.9968         = Validation score   (-mean_absolute_error)
        60.82s   = Training   runtime
        2.25s    = Validation runtime
Fitting model: NeuralNetTorch_BAG_L1 … Training model for up to 2221.47s of
the 2221.47s of remaining time.
```

```
        Fitting 8 child models (S3F1 - S3F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -87.4885         = Validation score   (-mean_absolute_error)
        315.46s  = Training   runtime
        0.93s    = Validation runtime
Fitting model: LightGBMLarge_BAG_L1 … Training model for up to 2106.2s of the
2106.2s of remaining time.
        Fitting 8 child models (S3F1 - S3F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -89.711  = Validation score   (-mean_absolute_error)
        279.59s  = Training   runtime
        65.43s   = Validation runtime
Repeating k-fold bagging: 4/20
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 1992.05s of the
1992.05s of remaining time.
        Fitting 8 child models (S4F1 - S4F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -86.7149         = Validation score   (-mean_absolute_error)
        113.89s  = Training   runtime
        70.9s    = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 1953.48s of the
1953.48s of remaining time.
        Fitting 8 child models (S4F1 - S4F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -91.775  = Validation score   (-mean_absolute_error)
        88.5s    = Training   runtime
        16.52s   = Validation runtime
Fitting model: CatBoost_BAG_L1 … Training model for up to 1924.3s of the
1924.3s of remaining time.
        Fitting 8 child models (S4F1 - S4F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -99.2807         = Validation score   (-mean_absolute_error)
        760.25s  = Training   runtime
        0.35s    = Validation runtime
Fitting model: NeuralNetFastAI_BAG_L1 … Training model for up to 1730.63s of
the 1730.63s of remaining time.
        Fitting 8 child models (S4F1 - S4F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -104.7171        = Validation score   (-mean_absolute_error)
        150.36s  = Training   runtime
        1.91s    = Validation runtime
Fitting model: XGBoost_BAG_L1 … Training model for up to 1689.96s of the
1689.96s of remaining time.
        Fitting 8 child models (S4F1 - S4F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -98.0495         = Validation score   (-mean_absolute_error)
        70.59s   = Training   runtime
        2.63s    = Validation runtime
```

```
Fitting model: NeuralNetTorch_BAG_L1 … Training model for up to 1677.39s of
the 1677.39s of remaining time.
        Fitting 8 child models (S4F1 - S4F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -87.2963         = Validation score   (-mean_absolute_error)
        412.32s  = Training   runtime
        1.24s    = Validation runtime
Fitting model: LightGBMLarge_BAG_L1 … Training model for up to 1578.39s of the
1578.39s of remaining time.
        Fitting 8 child models (S4F1 - S4F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -89.5168         = Validation score   (-mean_absolute_error)
        373.58s  = Training   runtime
        85.97s   = Validation runtime
Repeating k-fold bagging: 5/20
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 1461.81s of the
1461.81s of remaining time.
        Fitting 8 child models (S5F1 - S5F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -86.5869         = Validation score   (-mean_absolute_error)
        143.26s  = Training   runtime
        89.66s   = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 1421.47s of the
1421.46s of remaining time.
        Fitting 8 child models (S5F1 - S5F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -91.8165         = Validation score   (-mean_absolute_error)
        112.87s  = Training   runtime
        21.32s   = Validation runtime
Fitting model: CatBoost_BAG_L1 … Training model for up to 1390.24s of the
1390.24s of remaining time.
        Fitting 8 child models (S5F1 - S5F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -99.3817         = Validation score   (-mean_absolute_error)
        938.97s  = Training   runtime
        0.44s    = Validation runtime
Fitting model: NeuralNetFastAI_BAG_L1 … Training model for up to 1209.95s of
the 1209.94s of remaining time.
        Fitting 8 child models (S5F1 - S5F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -104.6388        = Validation score   (-mean_absolute_error)
        188.45s  = Training   runtime
        2.39s    = Validation runtime
Fitting model: XGBoost_BAG_L1 … Training model for up to 1168.67s of the
1168.66s of remaining time.
        Fitting 8 child models (S5F1 - S5F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -98.4477         = Validation score   (-mean_absolute_error)
```

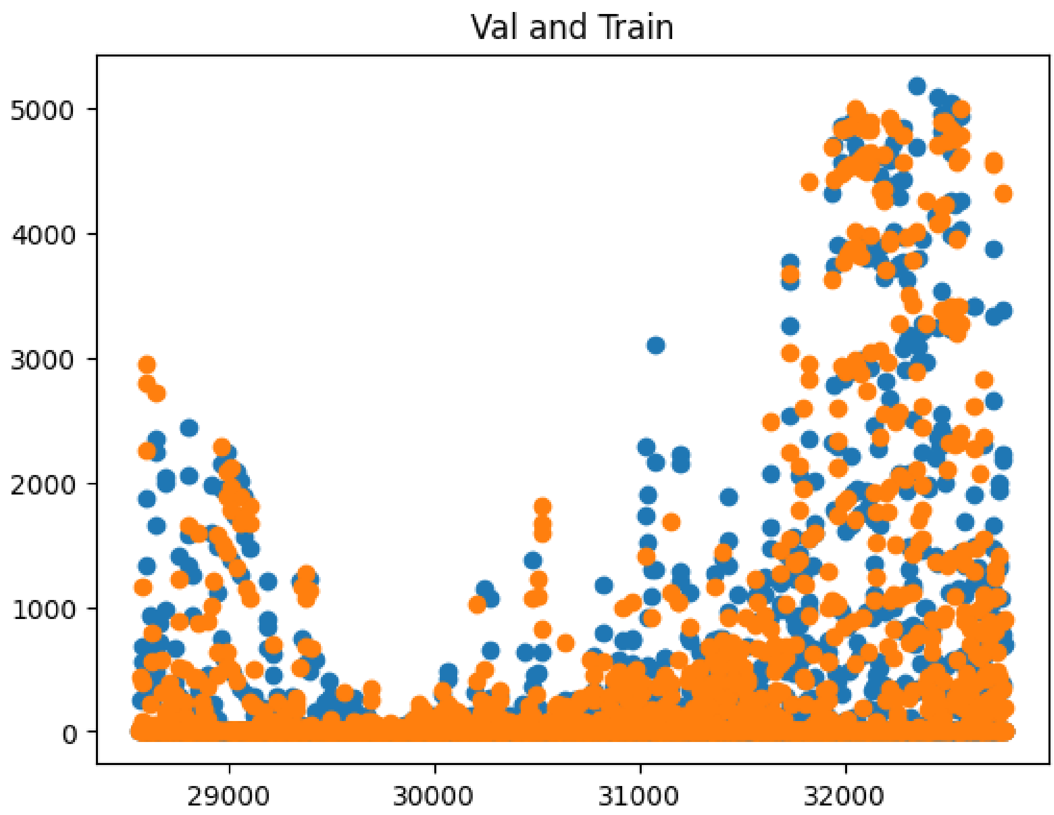
```
        75.52s   = Training   runtime
        2.85s    = Validation runtime
Fitting model: NeuralNetTorch_BAG_L1 … Training model for up to 1160.83s of
the 1160.83s of remaining time.
        Fitting 8 child models (S5F1 - S5F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -87.0783         = Validation score   (-mean_absolute_error)
        518.93s  = Training   runtime
        1.61s    = Validation runtime
Fitting model: LightGBMLarge_BAG_L1 … Training model for up to 1051.94s of the
1051.94s of remaining time.
        Fitting 8 child models (S5F1 - S5F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -89.4969         = Validation score   (-mean_absolute_error)
        468.04s  = Training   runtime
        107.97s  = Validation runtime
Repeating k-fold bagging: 6/20
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 929.95s of the
929.95s of remaining time.
        Fitting 8 child models (S6F1 - S6F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -86.5213         = Validation score   (-mean_absolute_error)
        171.91s  = Training   runtime
        105.88s  = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 889.28s of the
889.27s of remaining time.
        Fitting 8 child models (S6F1 - S6F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -91.9025         = Validation score   (-mean_absolute_error)
        134.45s  = Training   runtime
        26.98s   = Validation runtime
Fitting model: CatBoost_BAG_L1 … Training model for up to 859.92s of the
859.92s of remaining time.
        Fitting 8 child models (S6F1 - S6F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -99.4055         = Validation score   (-mean_absolute_error)
        1125.25s         = Training   runtime
        0.52s    = Validation runtime
Fitting model: NeuralNetFastAI_BAG_L1 … Training model for up to 672.0s of the
672.0s of remaining time.
        Fitting 8 child models (S6F1 - S6F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -104.7924        = Validation score   (-mean_absolute_error)
        226.54s  = Training   runtime
        2.89s    = Validation runtime
Fitting model: XGBoost_BAG_L1 … Training model for up to 630.36s of the
630.36s of remaining time.
        Fitting 8 child models (S6F1 - S6F8) | Fitting with
```

```
ParallelLocalFoldFittingStrategy
        -98.5432         = Validation score   (-mean_absolute_error)
        121.26s  = Training   runtime
        4.3s     = Validation runtime
Fitting model: NeuralNetTorch_BAG_L1 … Training model for up to 580.37s of the
580.37s of remaining time.
        Fitting 8 child models (S6F1 - S6F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -86.9082         = Validation score   (-mean_absolute_error)
        616.47s  = Training   runtime
        2.0s     = Validation runtime
Fitting model: LightGBMLarge_BAG_L1 … Training model for up to 480.3s of the
480.3s of remaining time.
        Fitting 8 child models (S6F1 - S6F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -89.3971         = Validation score   (-mean_absolute_error)
        561.25s  = Training   runtime
        128.74s  = Validation runtime
Completed 6/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L2 … Training model for up to 360.0s of the
356.36s of remaining time.
        -83.0054         = Validation score   (-mean_absolute_error)
        0.41s    = Training   runtime
        0.0s     = Validation runtime
AutoGluon training complete, total runtime = 3244.08s … Best model:
"WeightedEnsemble_L2"
TabularPredictor saved. To load, use: predictor =
TabularPredictor.load("AutogluonModels/submission_106_A/")
```

[18]:

```python
import matplotlib.pyplot as plt
leaderboards = [None, None, None]
def leaderboard_for_location(i, loc):
    if use_tune_data:
        plt.scatter(train_data[(train_data["location"] == loc) &␣
 ↪(train_data["is_estimated"]==True)]["y"].index,␣
 ↪train_data[(train_data["location"] == loc) &␣
 ↪(train_data["is_estimated"]==True)]["y"])
        plt.scatter(tuning_data[tuning_data["location"] == loc]["y"].index,␣
 ↪tuning_data[tuning_data["location"] == loc]["y"])
        plt.title("Val and Train")
        plt.show()

        if use_test_data:
            lb = predictors[i].leaderboard(test_data[test_data["location"] ==␣
 ↪loc])
            lb["location"] = loc
```

```
            plt.scatter(test_data[test_data["location"] == loc]["y"].index,␣
↪test_data[test_data["location"] == loc]["y"])
            plt.title("Test")

            return lb

    return pd.DataFrame()

leaderboards[0] = leaderboard_for_location(0, loc)
```



[19]:
```
loc = "B"
predictors[1] = fit_predictor_for_location(loc)
leaderboards[1] = leaderboard_for_location(1, loc)
```

```
Beginning AutoGluon training … Time limit = 3600s
AutoGluon will save models to "AutogluonModels/submission_106_B/"
AutoGluon Version:  0.8.2
Python Version:     3.10.12
Operating System:   Linux
Platform Machine:   x86_64
Platform Version:   #1 SMP Debian 5.10.197-1 (2023-09-29)
```

```
Disk Space Avail:   77.90 GB / 315.93 GB (24.7%)
Train Data Rows:    27448
Train Data Columns: 32
Tuning Data Rows:    1775
Tuning Data Columns: 32
Label Column: y
Preprocessing data …
AutoGluon infers your prediction problem is: 'regression' (because dtype of
label-column == float and many unique label-values observed).
        Label info (max, min, mean, stddev): (1152.3, -0.0, 97.84102, 206.22836)
        If 'regression' is not the correct problem_type, please manually specify
the problem_type parameter during predictor init (You may specify problem_type
as one of: ['binary', 'multiclass', 'regression'])
Using Feature Generators to preprocess the data …
Fitting AutoMLPipelineFeatureGenerator…
        Available Memory:                    126595.63 MB
        Train Data (Original)  Memory Usage: 8.94 MB (0.0% of available memory)
        Inferring data type of each feature based on column values. Set
feature_metadata_in to manually specify special dtypes of the features.
        Stage 1 Generators:
                Fitting AsTypeFeatureGenerator…
                        Note: Converting 1 features to boolean dtype as they
only contain 2 unique values.
        Stage 2 Generators:
                Fitting FillNaFeatureGenerator…
        Stage 3 Generators:
                Fitting IdentityFeatureGenerator…
        Stage 4 Generators:
                Fitting DropUniqueFeatureGenerator…
        Stage 5 Generators:
                Fitting DropDuplicatesFeatureGenerator…
        Useless Original Features (Count: 2): ['elevation:m', 'location']
                These features carry no predictive signal and should be manually
investigated.
                This is typically a feature which has the same value for all
rows.
                These features do not need to be present at inference time.
        Types of features in original data (raw dtype, special dtypes):
                ('float', []) : 29 | ['ceiling_height_agl:m',
'clear_sky_energy_1h:J', 'clear_sky_rad:W', 'cloud_base_agl:m', 'diffuse_rad:W',
…]
                ('int', [])   :  1 | ['is_estimated']
        Types of features in processed data (raw dtype, special dtypes):
                ('float', [])     : 29 | ['ceiling_height_agl:m',
'clear_sky_energy_1h:J', 'clear_sky_rad:W', 'cloud_base_agl:m', 'diffuse_rad:W',
…]
                ('int', ['bool']) :  1 | ['is_estimated']
        0.1s = Fit runtime
```

```
        30 features in original data used to generate 30 features in processed
data.
        Train Data (Processed) Memory Usage: 6.81 MB (0.0% of available memory)
Data preprocessing and feature engineering runtime = 0.14s …
AutoGluon will gauge predictive performance using evaluation metric:
'mean_absolute_error'
        This metric's sign has been flipped to adhere to being higher_is_better.
The metric score can be multiplied by -1 to get the metric value.
        To change this, specify the eval_metric parameter of Predictor()
use_bag_holdout=True, will use tuning_data as holdout (will not be used for
early stopping).
User-specified model hyperparameters to be fit:
{
        'NN_TORCH': {},
        'GBM': [{'extra_trees': True, 'ag_args': {'name_suffix': 'XT'}}, {},
'GBMLarge'],
        'CAT': {},
        'XGB': {},
        'FASTAI': {},
        'RF': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'XT': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'KNN': [{'weights': 'uniform', 'ag_args': {'name_suffix': 'Unif'}},
{'weights': 'distance', 'ag_args': {'name_suffix': 'Dist'}}],
}
Fitting 11 L1 models …
Fitting model: KNeighborsUnif_BAG_L1 … Training model for up to 3599.86s of
the 3599.86s of remaining time.
```

```
Training model for location B…
```

```
        -28.7463         = Validation score   (-mean_absolute_error)
        0.02s    = Training   runtime
        0.34s    = Validation runtime
Fitting model: KNeighborsDist_BAG_L1 … Training model for up to 3599.27s of
the 3599.27s of remaining time.
        -28.8771         = Validation score   (-mean_absolute_error)
        0.03s    = Training   runtime
        0.33s    = Validation runtime
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 3598.85s of the
3598.85s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
```

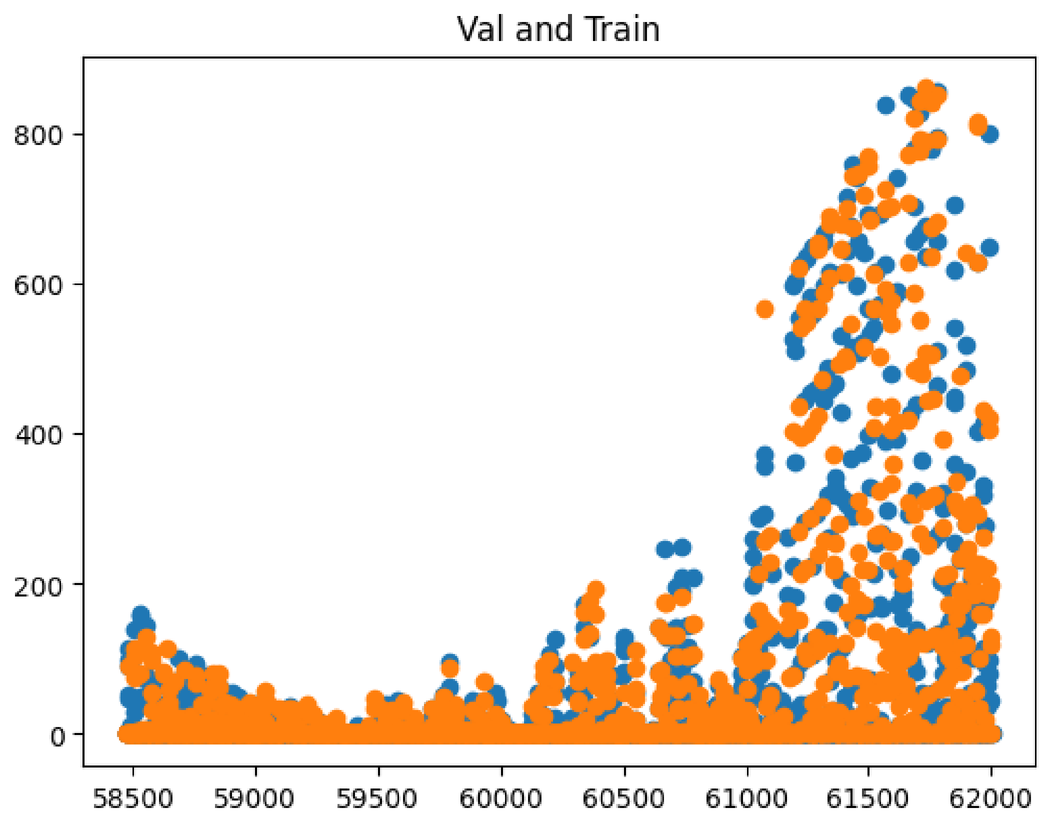
```
ParallelLocalFoldFittingStrategy
        -13.559  = Validation score   (-mean_absolute_error)
        27.84s   = Training   runtime
        17.46s   = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 3565.63s of the
3565.62s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -14.0715         = Validation score   (-mean_absolute_error)
        26.23s   = Training   runtime
        11.69s   = Validation runtime
Fitting model: RandomForestMSE_BAG_L1 … Training model for up to 3534.78s of
the 3534.78s of remaining time.
        -15.3559         = Validation score   (-mean_absolute_error)
        5.63s    = Training   runtime
        0.85s    = Validation runtime
Fitting model: CatBoost_BAG_L1 … Training model for up to 3527.44s of the
3527.44s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -14.6316         = Validation score   (-mean_absolute_error)
        190.45s  = Training   runtime
        0.09s    = Validation runtime
Fitting model: ExtraTreesMSE_BAG_L1 … Training model for up to 3335.68s of the
3335.68s of remaining time.
        -15.3744         = Validation score   (-mean_absolute_error)
        1.18s    = Training   runtime
        0.86s    = Validation runtime
Fitting model: NeuralNetFastAI_BAG_L1 … Training model for up to 3332.74s of
the 3332.74s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -14.7739         = Validation score   (-mean_absolute_error)
        34.61s   = Training   runtime
        0.43s    = Validation runtime
Fitting model: XGBoost_BAG_L1 … Training model for up to 3296.53s of the
3296.52s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -14.2926         = Validation score   (-mean_absolute_error)
        48.79s   = Training   runtime
        5.07s    = Validation runtime
Fitting model: NeuralNetTorch_BAG_L1 … Training model for up to 3243.73s of
the 3243.73s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.0711         = Validation score   (-mean_absolute_error)
        125.74s  = Training   runtime
```

```
        0.31s    = Validation runtime
Fitting model: LightGBMLarge_BAG_L1 … Training model for up to 3116.6s of the
3116.6s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.8297         = Validation score   (-mean_absolute_error)
        92.4s    = Training   runtime
        16.52s   = Validation runtime
Repeating k-fold bagging: 2/20
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 3015.19s of the
3015.18s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.5183         = Validation score   (-mean_absolute_error)
        55.86s   = Training   runtime
        36.38s   = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 2980.23s of the
2980.22s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -14.4785         = Validation score   (-mean_absolute_error)
        383.93s  = Training   runtime
        0.18s    = Validation runtime
Fitting model: NeuralNetFastAI_BAG_L1 … Training model for up to 2752.59s of
the 2752.59s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -14.7866         = Validation score   (-mean_absolute_error)
        68.84s   = Training   runtime
        0.88s    = Validation runtime
Fitting model: XGBoost_BAG_L1 … Training model for up to 2716.45s of the
2716.45s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -14.1882         = Validation score   (-mean_absolute_error)
        95.37s   = Training   runtime
        9.24s    = Validation runtime
Fitting model: NeuralNetTorch_BAG_L1 … Training model for up to 2664.89s of
the 2664.89s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.0109         = Validation score   (-mean_absolute_error)
        256.09s  = Training   runtime
        0.59s    = Validation runtime
Fitting model: LightGBMLarge_BAG_L1 … Training model for up to 2532.95s of the
2532.94s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
```

```
        -13.7182         = Validation score   (-mean_absolute_error)
        184.41s  = Training   runtime
        34.45s   = Validation runtime
Repeating k-fold bagging: 3/20
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 2426.62s of the
2426.62s of remaining time.
        Fitting 8 child models (S3F1 - S3F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.4621         = Validation score   (-mean_absolute_error)
        83.11s   = Training   runtime
        52.96s   = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 2391.26s of the
2391.26s of remaining time.
        Fitting 8 child models (S3F1 - S3F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -14.1175         = Validation score   (-mean_absolute_error)
        77.38s   = Training   runtime
        30.2s    = Validation runtime
Fitting model: CatBoost_BAG_L1 … Training model for up to 2360.97s of the
2360.97s of remaining time.
        Fitting 8 child models (S3F1 - S3F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -14.7601         = Validation score   (-mean_absolute_error)
        103.01s  = Training   runtime
        1.3s     = Validation runtime
Fitting model: XGBoost_BAG_L1 … Training model for up to 2133.12s of the
2133.12s of remaining time.
        Fitting 8 child models (S3F1 - S3F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -14.1966         = Validation score   (-mean_absolute_error)
        142.37s  = Training   runtime
        14.43s   = Validation runtime
Fitting model: NeuralNetTorch_BAG_L1 … Training model for up to 2079.98s of
the 2079.97s of remaining time.
        Fitting 8 child models (S3F1 - S3F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.4987         = Validation score   (-mean_absolute_error)
        110.55s  = Training   runtime
        66.86s   = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 1786.29s of the
1786.29s of remaining time.
        Fitting 8 child models (S4F1 - S4F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -14.089  = Validation score   (-mean_absolute_error)
        101.99s  = Training   runtime
        36.13s   = Validation runtime
Fitting model: CatBoost_BAG_L1 … Training model for up to 1754.63s of the
1754.63s of remaining time.
```

```
        Fitting 8 child models (S4F1 - S4F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -14.4445         = Validation score   (-mean_absolute_error)
        763.42s  = Training   runtime
        0.37s    = Validation runtime
Fitting model: NeuralNetFastAI_BAG_L1 … Training model for up to 1563.52s of
the 1563.52s of remaining time.
        Fitting 8 child models (S4F1 - S4F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -14.7304         = Validation score   (-mean_absolute_error)
        137.21s  = Training   runtime
        1.72s    = Validation runtime
Fitting model: XGBoost_BAG_L1 … Training model for up to 1526.67s of the
1526.67s of remaining time.
        Fitting 8 child models (S4F1 - S4F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -14.2089         = Validation score   (-mean_absolute_error)
        206.56s  = Training   runtime
        20.67s   = Validation runtime
Fitting model: NeuralNetTorch_BAG_L1 … Training model for up to 1454.99s of
the 1454.99s of remaining time.
        Fitting 8 child models (S4F1 - S4F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.0347         = Validation score   (-mean_absolute_error)
        524.79s  = Training   runtime
        1.28s    = Validation runtime
Fitting model: LightGBMLarge_BAG_L1 … Training model for up to 1331.82s of the
1331.82s of remaining time.
        Fitting 8 child models (S4F1 - S4F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.6416         = Validation score   (-mean_absolute_error)
        365.12s  = Training   runtime
        71.57s   = Validation runtime
Repeating k-fold bagging: 5/20
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 1219.63s of the
1219.63s of remaining time.
        Fitting 8 child models (S5F1 - S5F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.5174         = Validation score   (-mean_absolute_error)
        138.2s   = Training   runtime
        80.81s   = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 1181.8s of the
1181.8s of remaining time.
        Fitting 8 child models (S5F1 - S5F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -14.1019         = Validation score   (-mean_absolute_error)
        127.15s  = Training   runtime
        44.53s   = Validation runtime
```

```
Fitting model: CatBoost_BAG_L1 … Training model for up to 1148.15s of the
1148.15s of remaining time.
        Fitting 8 child models (S5F1 - S5F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -14.4162         = Validation score   (-mean_absolute_error)
        954.71s  = Training   runtime
        0.46s    = Validation runtime
Fitting model: NeuralNetFastAI_BAG_L1 … Training model for up to 955.31s of
the 955.31s of remaining time.
        Fitting 8 child models (S5F1 - S5F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -14.7257         = Validation score   (-mean_absolute_error)
        171.57s  = Training   runtime
        2.15s    = Validation runtime
Fitting model: XGBoost_BAG_L1 … Training model for up to 918.09s of the
918.09s of remaining time.
        Fitting 8 child models (S5F1 - S5F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -14.1986         = Validation score   (-mean_absolute_error)
        253.69s  = Training   runtime
        27.04s   = Validation runtime
Fitting model: NeuralNetTorch_BAG_L1 … Training model for up to 861.94s of the
861.94s of remaining time.
        Fitting 8 child models (S5F1 - S5F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.6019         = Validation score   (-mean_absolute_error)
        455.42s  = Training   runtime
        89.16s   = Validation runtime
Completed 5/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L2 … Training model for up to 360.0s of the
620.38s of remaining time.
        -12.3782         = Validation score   (-mean_absolute_error)
        0.4s     = Training   runtime
        0.0s     = Validation runtime
AutoGluon training complete, total runtime = 2980.04s … Best model:
"WeightedEnsemble_L2"
TabularPredictor saved. To load, use: predictor =
TabularPredictor.load("AutogluonModels/submission_106_B/")
```



[20]:
```
loc = "C"
predictors[2] = fit_predictor_for_location(loc)
leaderboards[2] = leaderboard_for_location(2, loc)
```

```
Beginning AutoGluon training … Time limit = 3600s
AutoGluon will save models to "AutogluonModels/submission_106_C/"
AutoGluon Version:  0.8.2
Python Version:     3.10.12
Operating System:   Linux
Platform Machine:   x86_64
Platform Version:   #1 SMP Debian 5.10.197-1 (2023-09-29)
Disk Space Avail:   69.23 GB / 315.93 GB (21.9%)
Train Data Rows:    24416
Train Data Columns: 32
Tuning Data Rows:    1498
Tuning Data Columns: 32
Label Column: y
Preprocessing data …
AutoGluon infers your prediction problem is: 'regression' (because dtype of
label-column == float and label-values can't be converted to int).
        Label info (max, min, mean, stddev): (999.6, 0.0, 80.50393, 169.1834)
```

```
        If 'regression' is not the correct problem_type, please manually specify
the problem_type parameter during predictor init (You may specify problem_type
as one of: ['binary', 'multiclass', 'regression'])
Using Feature Generators to preprocess the data …
Fitting AutoMLPipelineFeatureGenerator…
        Available Memory:                    126214.98 MB
        Train Data (Original)  Memory Usage: 7.93 MB (0.0% of available memory)
        Inferring data type of each feature based on column values. Set
feature_metadata_in to manually specify special dtypes of the features.
        Stage 1 Generators:
                Fitting AsTypeFeatureGenerator…
                        Note: Converting 1 features to boolean dtype as they
only contain 2 unique values.
        Stage 2 Generators:
                Fitting FillNaFeatureGenerator…
        Stage 3 Generators:
                Fitting IdentityFeatureGenerator…
        Stage 4 Generators:
                Fitting DropUniqueFeatureGenerator…
        Stage 5 Generators:
                Fitting DropDuplicatesFeatureGenerator…
        Useless Original Features (Count: 2): ['elevation:m', 'location']
                These features carry no predictive signal and should be manually
investigated.
                This is typically a feature which has the same value for all
rows.

Training model for location C…

                These features do not need to be present at inference time.
        Types of features in original data (raw dtype, special dtypes):
                ('float', []) : 29 | ['ceiling_height_agl:m',
'clear_sky_energy_1h:J', 'clear_sky_rad:W', 'cloud_base_agl:m', 'diffuse_rad:W',
…]
                ('int', [])   :  1 | ['is_estimated']
        Types of features in processed data (raw dtype, special dtypes):
                ('float', [])     : 29 | ['ceiling_height_agl:m',
'clear_sky_energy_1h:J', 'clear_sky_rad:W', 'cloud_base_agl:m', 'diffuse_rad:W',
…]
                ('int', ['bool']) :  1 | ['is_estimated']
        0.2s = Fit runtime
        30 features in original data used to generate 30 features in processed
data.
        Train Data (Processed) Memory Usage: 6.04 MB (0.0% of available memory)
Data preprocessing and feature engineering runtime = 0.19s …
AutoGluon will gauge predictive performance using evaluation metric:
'mean_absolute_error'
        This metric's sign has been flipped to adhere to being higher_is_better.
The metric score can be multiplied by -1 to get the metric value.
```

```
        To change this, specify the eval_metric parameter of Predictor()
use_bag_holdout=True, will use tuning_data as holdout (will not be used for
early stopping).
User-specified model hyperparameters to be fit:
{
        'NN_TORCH': {},
        'GBM': [{'extra_trees': True, 'ag_args': {'name_suffix': 'XT'}}, {},
'GBMLarge'],
        'CAT': {},
        'XGB': {},
        'FASTAI': {},
        'RF': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'XT': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'KNN': [{'weights': 'uniform', 'ag_args': {'name_suffix': 'Unif'}},
{'weights': 'distance', 'ag_args': {'name_suffix': 'Dist'}}],
}
Fitting 11 L1 models …
Fitting model: KNeighborsUnif_BAG_L1 … Training model for up to 3599.81s of
the 3599.81s of remaining time.
        -20.2712         = Validation score   (-mean_absolute_error)
        0.02s    = Training   runtime
        0.24s    = Validation runtime
Fitting model: KNeighborsDist_BAG_L1 … Training model for up to 3599.49s of
the 3599.49s of remaining time.
        -20.3511         = Validation score   (-mean_absolute_error)
        0.02s    = Training   runtime
        0.23s    = Validation runtime
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 3599.18s of the
3599.17s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -11.4751         = Validation score   (-mean_absolute_error)
        27.01s   = Training   runtime
        13.37s   = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 3567.37s of the
3567.36s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -12.6303         = Validation score   (-mean_absolute_error)
        25.17s   = Training   runtime
```

```
        6.29s    = Validation runtime
Fitting model: RandomForestMSE_BAG_L1 … Training model for up to 3538.38s of
the 3538.37s of remaining time.
        -16.654  = Validation score   (-mean_absolute_error)
        4.78s    = Training   runtime
        0.72s    = Validation runtime
Fitting model: CatBoost_BAG_L1 … Training model for up to 3532.29s of the
3532.29s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.0793         = Validation score   (-mean_absolute_error)
        65.79s   = Training   runtime
        8.14s    = Validation runtime
Fitting model: NeuralNetTorch_BAG_L1 … Training model for up to 3238.9s of the
3238.9s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -12.8026         = Validation score   (-mean_absolute_error)
        98.49s   = Training   runtime
        0.28s    = Validation runtime
Fitting model: LightGBMLarge_BAG_L1 … Training model for up to 3138.98s of the
3138.98s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -12.8213         = Validation score   (-mean_absolute_error)
        89.12s   = Training   runtime
        19.05s   = Validation runtime
Repeating k-fold bagging: 2/20
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 3040.25s of the
3040.24s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -11.4279         = Validation score   (-mean_absolute_error)
        53.54s   = Training   runtime
        25.05s   = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 3008.39s of the
3008.39s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -12.5184         = Validation score   (-mean_absolute_error)
        49.85s   = Training   runtime
        14.43s   = Validation runtime
Fitting model: CatBoost_BAG_L1 … Training model for up to 2978.58s of the
2978.58s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -12.6037         = Validation score   (-mean_absolute_error)
        375.27s  = Training   runtime
```

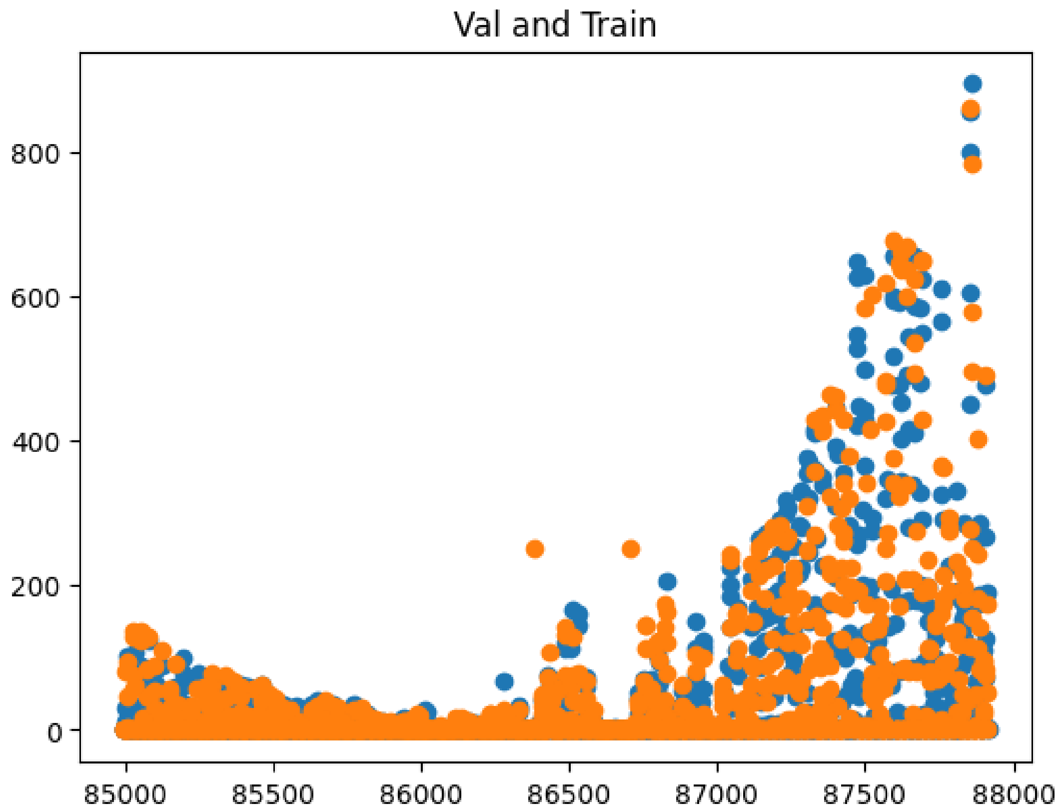
```
        0.15s    = Validation runtime
Fitting model: NeuralNetFastAI_BAG_L1 … Training model for up to 2789.58s of
the 2789.57s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -14.9735         = Validation score   (-mean_absolute_error)
        61.45s   = Training   runtime
        0.82s    = Validation runtime
Fitting model: XGBoost_BAG_L1 … Training model for up to 2757.09s of the
2757.08s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.078  = Validation score   (-mean_absolute_error)
        109.19s  = Training   runtime
        9.46s    = Validation runtime
Fitting model: NeuralNetTorch_BAG_L1 … Training model for up to 2709.23s of
the 2709.23s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -12.924  = Validation score   (-mean_absolute_error)
        183.89s  = Training   runtime
        0.54s    = Validation runtime
Fitting model: LightGBMLarge_BAG_L1 … Training model for up to 2622.22s of the
2622.22s of remaining time.
        Fitting 8 child models (S2F1 - S2F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -12.7484         = Validation score   (-mean_absolute_error)
        180.32s  = Training   runtime
        33.34s   = Validation runtime
Repeating k-fold bagging: 3/20
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 2518.76s of the
2518.76s of remaining time.
        Fitting 8 child models (S3F1 - S3F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -11.4519         = Validation score   (-mean_absolute_error)
        80.35s   = Training   runtime
        40.34s   = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 2484.85s of the
2484.84s of remaining time.
        Fitting 8 child models (S3F1 - S3F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -12.526  = Validation score   (-mean_absolute_error)
        75.35s   = Training   runtime
        25.35s   = Validation runtime
Fitting model: CatBoost_BAG_L1 … Training model for up to 2453.08s of the
2453.08s of remaining time.
        Fitting 8 child models (S3F1 - S3F8) | Fitting with
ParallelLocalFoldFittingStrategy
```

```
        -12.6167         = Validation score   (-mean_absolute_error)
        562.21s  = Training   runtime
        0.22s    = Validation runtime
Fitting model: NeuralNetFastAI_BAG_L1 … Training model for up to 2264.7s of
the 2264.7s of remaining time.
        Fitting 8 child models (S3F1 - S3F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -15.0014         = Validation score   (-mean_absolute_error)
        92.09s   = Training   runtime
        1.2s     = Validation runtime
Fitting model: XGBoost_BAG_L1 … Training model for up to 2231.94s of the
2231.94s of remaining time.
        Fitting 8 child models (S3F1 - S3F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.1295         = Validation score   (-mean_absolute_error)
        153.76s  = Training   runtime
        15.12s   = Validation runtime
Fitting model: NeuralNetTorch_BAG_L1 … Training model for up to 2181.4s of the
2181.39s of remaining time.
        Fitting 8 child models (S3F1 - S3F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -12.8658         = Validation score   (-mean_absolute_error)
        266.44s  = Training   runtime
        0.81s    = Validation runtime
Fitting model: LightGBMLarge_BAG_L1 … Training model for up to 2097.11s of the
2097.11s of remaining time.
        Fitting 8 child models (S3F1 - S3F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -12.7955         = Validation score   (-mean_absolute_error)
        270.26s  = Training   runtime
        48.8s    = Validation runtime
Repeating k-fold bagging: 4/20
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 1990.61s of the
1990.61s of remaining time.
        Fitting 8 child models (S4F1 - S4F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -11.4495         = Validation score   (-mean_absolute_error)
        106.01s  = Training   runtime
        52.76s   = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 1956.4s of the
1956.39s of remaining time.
        Fitting 8 child models (S4F1 - S4F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -12.5155         = Validation score   (-mean_absolute_error)
        102.09s  = Training   runtime
        37.95s   = Validation runtime
Fitting model: CatBoost_BAG_L1 … Training model for up to 1921.87s of the
1921.87s of remaining time.
```

```
        Fitting 8 child models (S4F1 - S4F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -12.6369         = Validation score   (-mean_absolute_error)
        748.34s  = Training   runtime
        0.29s    = Validation runtime
Fitting model: NeuralNetFastAI_BAG_L1 … Training model for up to 1734.21s of
the 1734.2s of remaining time.
        Fitting 8 child models (S4F1 - S4F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -15.034  = Validation score   (-mean_absolute_error)
        122.98s  = Training   runtime
        1.6s     = Validation runtime
Fitting model: XGBoost_BAG_L1 … Training model for up to 1700.76s of the
1700.76s of remaining time.
        Fitting 8 child models (S4F1 - S4F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.1093         = Validation score   (-mean_absolute_error)
        215.17s  = Training   runtime
        21.91s   = Validation runtime
Fitting model: NeuralNetTorch_BAG_L1 … Training model for up to 1632.44s of
the 1632.44s of remaining time.
        Fitting 8 child models (S4F1 - S4F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -12.8574         = Validation score   (-mean_absolute_error)
        356.34s  = Training   runtime
        1.09s    = Validation runtime
Fitting model: LightGBMLarge_BAG_L1 … Training model for up to 1540.55s of the
1540.55s of remaining time.
        Fitting 8 child models (S4F1 - S4F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -12.7854         = Validation score   (-mean_absolute_error)
        359.29s  = Training   runtime
        63.0s    = Validation runtime
Repeating k-fold bagging: 5/20
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 1432.16s of the
1432.16s of remaining time.
        Fitting 8 child models (S5F1 - S5F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -11.4396         = Validation score   (-mean_absolute_error)
        132.85s  = Training   runtime
        67.58s   = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 1395.04s of the
1395.04s of remaining time.
        Fitting 8 child models (S5F1 - S5F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -12.5085         = Validation score   (-mean_absolute_error)
        126.39s  = Training   runtime
        43.68s   = Validation runtime
```

```
Fitting model: CatBoost_BAG_L1 … Training model for up to 1362.13s of the
1362.13s of remaining time.
        Fitting 8 child models (S5F1 - S5F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -12.6382         = Validation score   (-mean_absolute_error)
        934.32s  = Training   runtime
        0.36s    = Validation runtime
Fitting model: NeuralNetFastAI_BAG_L1 … Training model for up to 1174.57s of
the 1174.57s of remaining time.
        Fitting 8 child models (S5F1 - S5F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -15.039  = Validation score   (-mean_absolute_error)
        153.73s  = Training   runtime
        2.02s    = Validation runtime
Fitting model: XGBoost_BAG_L1 … Training model for up to 1141.05s of the
1141.04s of remaining time.
        Fitting 8 child models (S5F1 - S5F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.1371         = Validation score   (-mean_absolute_error)
        258.48s  = Training   runtime
        24.18s   = Validation runtime
Fitting model: NeuralNetTorch_BAG_L1 … Training model for up to 1090.05s of
the 1090.04s of remaining time.
        Fitting 8 child models (S5F1 - S5F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -12.8069         = Validation score   (-mean_absolute_error)
        453.98s  = Training   runtime
        1.37s    = Validation runtime
Fitting model: LightGBMLarge_BAG_L1 … Training model for up to 990.22s of the
990.22s of remaining time.
        Fitting 8 child models (S5F1 - S5F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -12.7775         = Validation score   (-mean_absolute_error)
        448.98s  = Training   runtime
        77.52s   = Validation runtime
Repeating k-fold bagging: 6/20
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 877.27s of the
877.27s of remaining time.
        Fitting 8 child models (S6F1 - S6F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -11.4493         = Validation score   (-mean_absolute_error)
        158.74s  = Training   runtime
        79.27s   = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 840.32s of the
840.32s of remaining time.
        Fitting 8 child models (S6F1 - S6F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -12.4794         = Validation score   (-mean_absolute_error)
```

```
        153.33s  = Training   runtime
        51.41s   = Validation runtime
Fitting model: CatBoost_BAG_L1 … Training model for up to 805.15s of the
805.15s of remaining time.
        Fitting 8 child models (S6F1 - S6F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -12.6425         = Validation score   (-mean_absolute_error)
        1120.1s  = Training   runtime
        0.43s    = Validation runtime
Fitting model: NeuralNetFastAI_BAG_L1 … Training model for up to 617.66s of
the 617.65s of remaining time.
        Fitting 8 child models (S6F1 - S6F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -15.0319         = Validation score   (-mean_absolute_error)
        184.43s  = Training   runtime
        2.41s    = Validation runtime
Fitting model: XGBoost_BAG_L1 … Training model for up to 583.8s of the 583.8s
of remaining time.
        Fitting 8 child models (S6F1 - S6F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -13.0914         = Validation score   (-mean_absolute_error)
        304.9s   = Training   runtime
        30.23s   = Validation runtime
Fitting model: NeuralNetTorch_BAG_L1 … Training model for up to 528.15s of the
528.15s of remaining time.
        Fitting 8 child models (S6F1 - S6F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -12.8484         = Validation score   (-mean_absolute_error)
        541.49s  = Training   runtime
        1.63s    = Validation runtime
Fitting model: LightGBMLarge_BAG_L1 … Training model for up to 438.31s of the
438.3s of remaining time.
        Fitting 8 child models (S6F1 - S6F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -12.768  = Validation score   (-mean_absolute_error)
        539.04s  = Training   runtime
        93.89s   = Validation runtime
Completed 6/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L2 … Training model for up to 360.0s of the
320.97s of remaining time.
        -11.3038         = Validation score   (-mean_absolute_error)
        0.41s    = Training   runtime
        0.0s     = Validation runtime
AutoGluon training complete, total runtime = 3279.46s … Best model:
"WeightedEnsemble_L2"
TabularPredictor saved. To load, use: predictor =
TabularPredictor.load("AutogluonModels/submission_106_C/")
```



[21]:
```
# save leaderboards to csv
pd.concat(leaderboards).to_csv(f"leaderboards/{new_filename}.csv")
```

5 Submit

[22]:
```
import pandas as pd
import matplotlib.pyplot as plt

future_test_data = TabularDataset('X_test_raw.csv')
future_test_data["ds"] = pd.to_datetime(future_test_data["ds"])
#test_data
```

```
Loaded data from: X_test_raw.csv | Columns = 33 / 33 | Rows = 4608 -> 4608
```

[23]:
```
test_ids = TabularDataset('test.csv')
test_ids["time"] = pd.to_datetime(test_ids["time"])
# merge test_data with test_ids
future_test_data_merged = pd.merge(future_test_data, test_ids, how="inner",␣
↪right_on=["time", "location"], left_on=["ds", "location"])
```

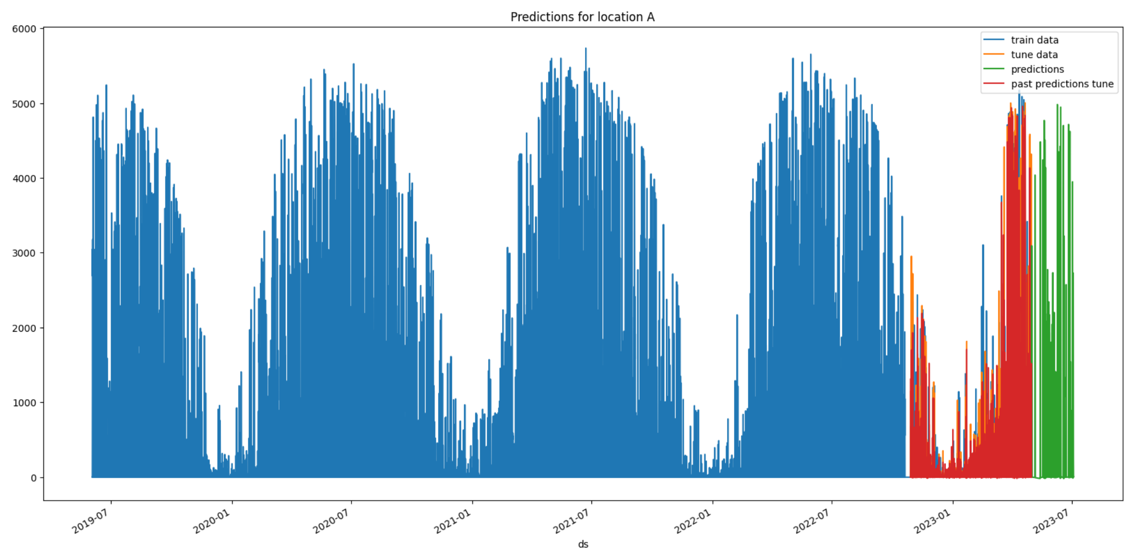
```
#test_data_merged
```

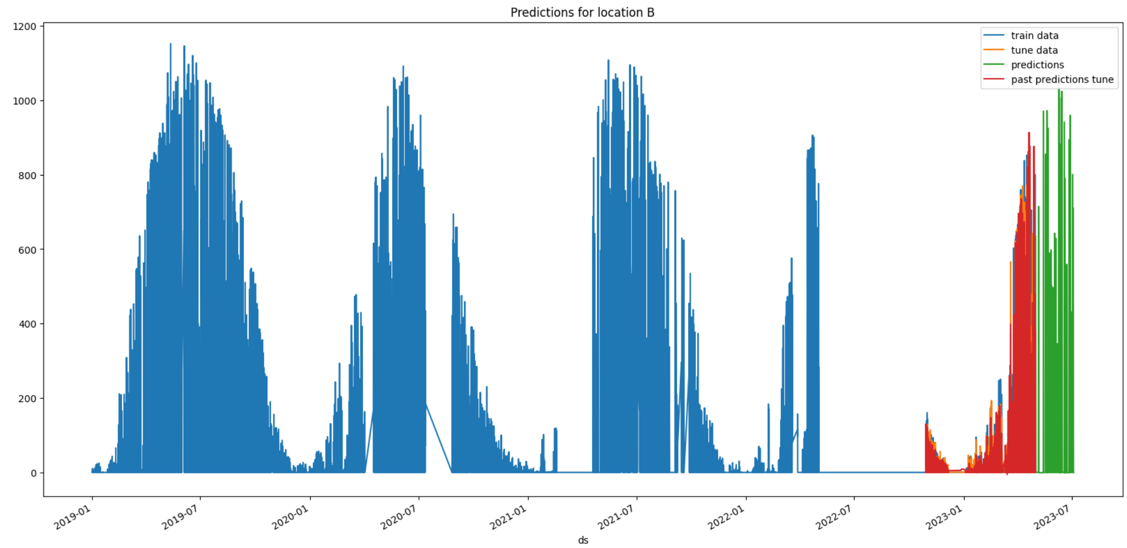
```
Loaded data from: test.csv | Columns = 4 / 4 | Rows = 2160 -> 2160
```

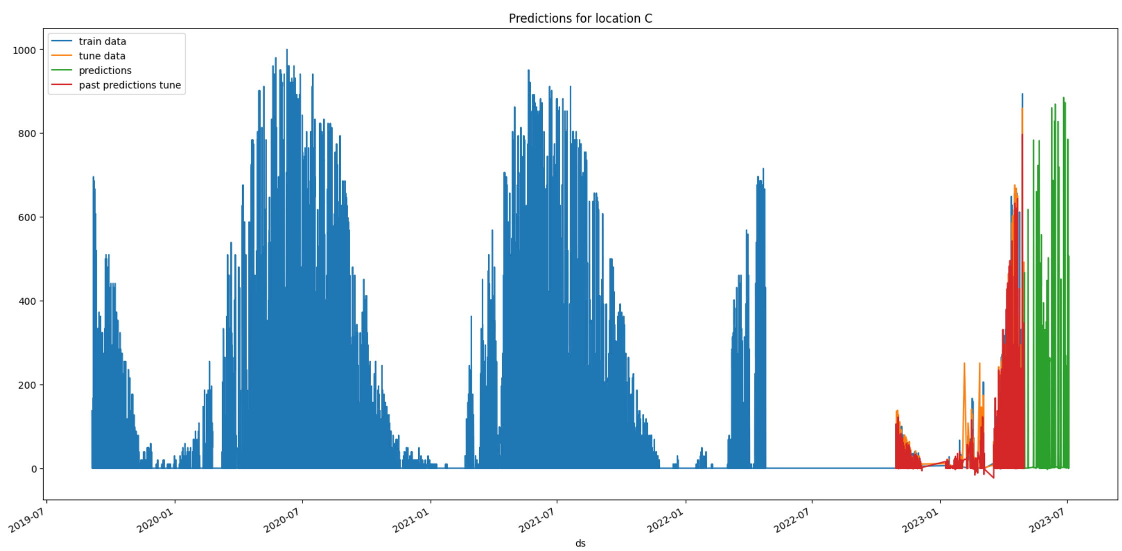
[24]:
```
# predict, grouped by location
predictions = []
location_map = {
    "A": 0,
    "B": 1,
    "C": 2
}
for loc, group in future_test_data.groupby('location'):
    i = location_map[loc]
    subset = future_test_data_merged[future_test_data_merged["location"] ==␣
 ↪loc].reset_index(drop=True)
    #print(subset)
    pred = predictors[i].predict(subset)
    subset["prediction"] = pred
    predictions.append(subset)

    # get past predictions
    #train_data.loc[train_data["location"] == loc, "prediction"] = ␣
 ↪predictors[i].predict(train_data[train_data["location"] == loc])
    if use_tune_data:
        tuning_data.loc[tuning_data["location"] == loc, "prediction"] = ␣
 ↪predictors[i].predict(tuning_data[tuning_data["location"] == loc])
    if use_test_data:
        test_data.loc[test_data["location"] == loc, "prediction"] = ␣
 ↪predictors[i].predict(test_data[test_data["location"] == loc])
```

[25]:
```
# plot predictions for location A, in addition to train data for A
for loc, idx in location_map.items():
    fig, ax = plt.subplots(figsize=(20, 10))
    # plot train data
    train_data[train_data["location"]==loc].plot(x='ds', y='y', ax=ax,␣
 ↪label="train data")
    if use_tune_data:
        tuning_data[tuning_data["location"]==loc].plot(x='ds', y='y', ax=ax,␣
 ↪label="tune data")
    if use_test_data:
        test_data[test_data["location"]==loc].plot(x='ds', y='y', ax=ax,␣
 ↪label="test data")

    # plot predictions
    predictions[idx].plot(x='ds', y='prediction', ax=ax, label="predictions")

    # plot past predictions
```

```
    #train_data_with_dates[train_data_with_dates["location"]==loc].plot(x='ds',␣
↪y='prediction', ax=ax, label="past predictions")
    #train_data[train_data["location"]==loc].plot(x='ds', y='prediction',␣
↪ax=ax, label="past predictions train")
    if use_tune_data:
        tuning_data[tuning_data["location"]==loc].plot(x='ds', y='prediction',␣
↪ax=ax, label="past predictions tune")
    if use_test_data:
        test_data[test_data["location"]==loc].plot(x='ds', y='prediction',␣
↪ax=ax, label="past predictions test")


    # title
    ax.set_title(f"Predictions for location {loc}")
```







[26]:
```
temp_predictions = [prediction.copy() for prediction in predictions]
if clip_predictions:
    # clip predictions smaller than 0 to 0
    for pred in temp_predictions:
        # print smallest prediction
        print("Smallest prediction:", pred["prediction"].min())
        pred.loc[pred["prediction"] < 0, "prediction"] = 0
        print("Smallest prediction after clipping:", pred["prediction"].min())
```

```
# Instead of clipping, shift all prediction values up by the largest negative␣
↪number.
# This way, the smallest prediction will be 0.
elif shift_predictions:
    for pred in temp_predictions:
        # print smallest prediction
        print("Smallest prediction:", pred["prediction"].min())
        pred["prediction"] = pred["prediction"] - pred["prediction"].min()
        print("Smallest prediction after clipping:", pred["prediction"].min())

elif shift_predictions_by_average_of_negatives_then_clip:
    for pred in temp_predictions:
        # print smallest prediction
        print("Smallest prediction:", pred["prediction"].min())
        mean_negative = pred[pred["prediction"] < 0]["prediction"].mean()
        # if not nan
        if mean_negative == mean_negative:
            pred["prediction"] = pred["prediction"] - mean_negative

        pred.loc[pred["prediction"] < 0, "prediction"] = 0
        print("Smallest prediction after clipping:", pred["prediction"].min())



# concatenate predictions
submissions_df = pd.concat(temp_predictions)
submissions_df = submissions_df[["id", "prediction"]]
submissions_df
```

```
Smallest prediction: -19.063887
Smallest prediction after clipping: 0.0
Smallest prediction: -1.5246444
Smallest prediction after clipping: 0.0
Smallest prediction: -3.1010737
Smallest prediction after clipping: 0.0
```

[26]:

```
       id  prediction
0       0    0.000000
1       1    0.000000
2       2    0.000000
3       3   22.159822
4       4  348.690765
..    …         …
715  2155   71.288185
716  2156   40.849781
717  2157   11.144910
718  2158    1.808917
```

```
719  2159    0.845557

[2160 rows x 2 columns]
```

[27]:
```
# Save the submission DataFrame to submissions folder, create new name based on␣
↪last submission, format is submission_<last_submission_number + 1>.csv

# Save the submission
print(f"Saving submission to submissions/{new_filename}.csv")
submissions_df.to_csv(os.path.join('submissions', f"{new_filename}.csv"),␣
↪index=False)
print("jall1a")
```

```
Saving submission to submissions/submission_106.csv
jall1a
```

[28]:
```
# feature importance
# print starting calculating feature importance for location A with big text␣
↪font
print("\033[1m" + "Calculating feature importance for location A..." +␣
↪"\033[0m")
predictors[0].feature_importance(feature_stage="original",␣
↪data=test_data[test_data["location"] == "A"], time_limit=60*10)
print("\033[1m" + "Calculating feature importance for location B..." +␣
↪"\033[0m")
predictors[1].feature_importance(feature_stage="original",␣
↪data=test_data[test_data["location"] == "B"], time_limit=60*10)
print("\033[1m" + "Calculating feature importance for location C..." +␣
↪"\033[0m")
predictors[2].feature_importance(feature_stage="original",␣
↪data=test_data[test_data["location"] == "C"], time_limit=60*10)
```

Calculating feature importance for location A…

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
Cell In[28], line 4
      1 # feature importance
      2 # print starting calculating feature importance for location A with big␣
↪text font
      3 print("\033[1m" + "Calculating feature importance for location A…" +␣
↪"\033[0m")
----> 4 predictors[0].feature_importance(feature_stage="original",␣
↪data=test_data[test_data["location"] == "A"], time_limit=60*10)
      5 print("\033[1m" + "Calculating feature importance for location B…" +␣
↪"\033[0m")
      6 predictors[1].feature_importance(feature_stage="original",␣
↪data=test_data[test_data["location"] == "B"], time_limit=60*10)
```

```
NameError: name 'test_data' is not defined
```

[ ]:
```python
# save this notebook to submissions folder
import subprocess
import os
#subprocess.run(["jupyter", "nbconvert", "--to", "pdf", "--output", os.path.
↪join('notebook_pdfs', f"{new_filename}_automatic_save.pdf"),␣
↪"autogluon_each_location.ipynb"])
subprocess.run(["jupyter", "nbconvert", "--to", "pdf", "--output", os.path.
↪join('notebook_pdfs', f"{new_filename}.pdf"), "autogluon_each_location.
↪ipynb"])
```

[ ]:
```python
# import subprocess

# def execute_git_command(directory, command):
#     """Execute a Git command in the specified directory."""
#     try:
#         result = subprocess.check_output(['git', '-C', directory] + command,␣
↪stderr=subprocess.STDOUT)
#         return result.decode('utf-8').strip(), True
#     except subprocess.CalledProcessError as e:
#         print(f"Git command failed with message: {e.output.decode('utf-8').
↪strip()}")
#         return e.output.decode('utf-8').strip(), False

# git_repo_path = "."

# execute_git_command(git_repo_path, ['config', 'user.email',␣
↪'henrikskog01@gmail.com'])
# execute_git_command(git_repo_path, ['config', 'user.name', hello if hello is␣
↪not None else 'Henrik eller Jørgen'])

# branch_name = new_filename

# # add datetime to branch name
# branch_name += f"_{pd.Timestamp.now().strftime('%Y-%m-%d_%H-%M-%S')}"

# commit_msg = "run result"

# execute_git_command(git_repo_path, ['checkout', '-b',branch_name])

# # Navigate to your repo and commit changes
# execute_git_command(git_repo_path, ['add', '.'])
# execute_git_command(git_repo_path, ['commit', '-m',commit_msg])
```

```
# # Push to remote
# output, success = execute_git_command(git_repo_path, ['push',␣
↪'origin',branch_name])

# # If the push fails, try setting an upstream branch and push again
# if not success and 'upstream' in output:
#     print("Attempting to set upstream and push again...")
#     execute_git_command(git_repo_path, ['push', '--set-upstream',␣
↪'origin',branch_name])
#     execute_git_command(git_repo_path, ['push', 'origin', 'henrik_branch'])

# execute_git_command(git_repo_path, ['checkout', 'main'])
```